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THE UNIVERSITY OF OKLAHOMA

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A COMPARISON OF DETERMINISTIC LOT SIZING TECHNIQUES USING FOCUS FORECASTS OF STOCHASTIC DEMAND DATA

A THESIS

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

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BRYAN STEWART CLINE

Norman, Oklahoma

1989

A COMPARISON OF DETERMINISTIC LOT SIZING TECHNIQUES

USING FOCUS FORECASTS OF STOCHASTIC DEMAND DATA

A THESIS

APPROVED FOR THE SCHOOL OF INDUSTRIAL ENGINEERING

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CHAPTER I

INTRODUCTION

A basic concern of any organization which manages production or inventory is the question "How much?", i.e., how much to produce or how much (inventory) to order? It is a very easy question to ask but not quite as easy to answer. (Saunders, 1987)

The difficulty stems from the nature of "consumer" demand. Specifically, future demand is seldom known with any degree of certainty ~~(Tsado, 1985a)~~. Anticipated demand is determined as best as possible using any one of a multitude of forecasting techniques and only then "plugged" into a production lot size heuristic. Unfortunately, if one subscribes to the theory that forecasts are usually wrong, then the old adage, "garbage in, garbage out", would tend to suggest there can never be an optimal solution.

Most research in this area has therefore concentrated on developing and/or modifying production lot size heuristics in the hopes of providing the next best thing, i.e., the "least wrong" answer. The result has been quite an array of techniques varying in both size (complexity) and scope (~~Ritchie and Tsado, 1986).~~

The problem left to industry is one of choice. Which heuristic is best? Several studies have been performed in an effort to answer this question as well. Some of these works include Benton and Whybark (1982); Callarman and Hamrin (1979, 1984); De Bodt (1983); De Bodt and Wassenhove (1983a, b); Tsado (1985a); Ritchie and Tsado (1986); Wemmerlöv and Whybark (1984). Most of these works, however, deal only with simulated demand data. And only Tsado (1985a) uses empirical demand data to "validate" the results obtained from simulated and published data. Unfortunately, he generates the forecasts for demand "artificially", i.e., given an analysis of the demand pattern over the entire demand history.

The importance of validating theoretical results (either analytical or simulated) should not be underestimated. For example, Flores and Whybark (1986) in their study of forecasting techniques have shown that significant differences can occur between the results found from synthetic, i.e., simulated, data and those obtained from empirical data. They state, "...the message to researchers rings clear: be careful in drawing "real-world" conclusions from laboratory data." Amar and Gupta (1986) state very much the same thing regarding their study of simulated and empirical demand on production scheduling algorithms: "Final claims about the superiority of [a] proposed methodology... can be settled only after sufficient experience with real life situations."

Further, all of these studies combined shortage costs (if included) and inventory and setup costs in the total cost calculation. As shortages may imply different "costs" to different organizations, it would be interesting to analyze these two types of costs separately. The need for further validation of previous studies of lot sizing techniques is therefore justified.

CHAPTER II

LITERATURE REVIEW

This chapter provides a review of the literature on basic lot sizing techniques and their application to stochastic demand. Material covering the lot size algorithms and forecast models used in this study is presented in Chapters III and IV, respectively.

Mathematical Models, Exponential Smoothing

Deterministic Demand Models

In order to determine what the optimal answer is to the question, "How much?", one must first examine the type of demand to be modeled. The most tractable demand model is, of course, constant or level demand. Therefore, if the relevant fixed costs (generally order or setup costs) and variable costs (generally inventory holding costs) are known, and:

1. demand is constant and deterministic,
2. the order quantity is assumed a continuous variable,
3. there are no quantity price breaks,
4. costs are relatively stable,

5. replenishment/production lead time is zero, and
6. no shortages or back orders are allowed,

the optimal (most economic) production or order quantity is easily derived by minimizing the total relevant costs (TRC) per unit time, i.e.,

$$TRC(Q) = \text{variable cost} + \text{fixed cost} = Q\,h/2 + A\,D/Q$$

where Q is the order or production quantity, h is the inventory holding cost expressed as cost per unit per period, or \$/unit/period, A is defined as the fixed set-up or order cost, and D is the demand rate of the item in units per unit time (from Silver and Peterson, 1985). Specifically, this economic order quantity, or EOQ, is given as:

$$EOQ = (2\,A\,D\,/\,h)^{\frac{1}{2}}$$

Once we relax the assumption of level demand and allow time variance, however, the EOQ is no longer guaranteed to provide an optimal solution.

This assumption of constant demand is one of the first problems we encounter with the basic EOQ model. Few manufacturers, suppliers, or retailers can expect to have requirements for exactly N units of a product every period over the entire product's life cycle. In fact, one would expect demand to (hopefully) increase from zero when a product is introduced, stabilize once initial demands are satisfied, and then (unfortunately) decrease as the product becomes obsolete. And, generally, this is the case.

Hofer (1977) defines the fundamental stages of product/market evolution similarly. However, all stages basically fall into three categories: linearly increasing demand, level demand, and linearly decreasing demand (Chalmet, De Bodt, and Van Wassenhove, 1985). These time varying levels of demand render the once optimal EOQ model to the level of a mere heuristic. (A heuristic is an algorithm which gives near optimal problem solutions.)

Although the Wagner and Whitten (1958) dynamic programming approach to the time varying demand model is guaranteed to provide an optimal solution, many authors feel this method is too complicated for general industrial use (McLaren, 1977; Silver, 1981; Wagner, 1980). In addition, the Wagner-Whitten algorithm may provide sub-optimal results when used in the context of a rolling demand horizon as normally used in industry (De Bodt and Wassenhove, 1983a). This "sub-optimality" results from violation of the assumption that demand after the last period in the horizon is zero. It is interesting to note, however, that objections to use of the Wagner-Whitten technique have steadily declined in the past several years primarily due to the general increase in the power of microcomputers and the advent of such efficient high level languages as C and PASCAL (Saydam and McKnew, 1987 ; Evans, 1985).

As a result, most work in this area has involved the development, test and evaluation of a multitude of (generally) simple heuristic policies in an attempt to provide solutions as "near-optimal" as possible. Some of these heuristics include EOQ, Silver-Meal, part-period balancing (Eisenhut), and least total cost to name a few.

All heuristics can be divided into three general classifications, specifically:

1. EOQ rules (which trade off order costs and holding costs per unit time, e.g., discrete EOQ),
2. Marginal cost rules (which equate marginal order and holding costs per period, e.g., Silver and Meal, 1973), and
3. Target rules (which set holding costs equal to a target, e.g., the part-period balance algorithm which increases the production lot size until the holding cost reaches a target equal to the ordering cost)

(From Wemmerlöv and Whybark, 1984).

Several studies have shown that various heuristics will perform differently under different types of conditions. In particular, Ritchie and Tsado (1986) have shown the best, most robust lot-size heuristics to be marginal cost (Groff, 1979), the simplified part-period (balance), and Silver-Meal algorithms. Further, they show that switching from one rule to another is not worthwhile, meaning it is generally better to use a good rule to begin with.

Therefore, given deterministic, time varying demand, the question of how much to produce or order seems to be relatively easy to answer. Unfortunately, we encounter a second problem with our assumptions on demand. One rarely knows with any certainty what future demands will be (Tsado, 1985a).

Stochastic Demand Models

Solution of the EOQ or lot size problem for stochastic demand is very difficult. As a result, most research in this area has focused on the relative performance of algorithms designed for deterministic demand as applied to stochastic demand over a rolling horizon (Benton and Whybark, 1982; Callarman,1979; Callarman and Hamrin, 1979, 1984; De Bodt and Wassenhove, 1983; Tsado, 1985a; Wemmerlöv and Whybark, 1984).

By rolling horizon, we mean that "lot sizing takes place over a fixed number of periods, the forecast horizon, and that only the first period's decision is implemented. Next period, a new fixed horizon problem is made, etc. (Baker and Peterson, 1979)." (From Wemmerlöv and Whybark, 1984.) The forecast horizon, in turn, is based on mean time between orders, or TBO, given by:

$$TBO = [(2A)/(D h)]^{\frac{1}{2}}$$

where A is the setup or holding cost, D is the average forecasted demand, and h is inventory holding cost. TBO, therefore, is dependent on the inventory ratio, i.e., A/h.

There is no one consensus on what values of A/h to use. In a problem presented by Berry (1972) and later used by many others, the value was 152.5. De Matteis (1968), on the other hand, used a factor of 100. (From Heemsbergen, 1987.) Tsado (1985) used a wide range of values, specifically:

7.5	10.0	30.0	50.0	70.0
90.0	110.0	130.0	150.0	170.0

Ritchie and Tsado (1986) used a value of 400! The reasons why the literature is so inconsistent are not quite clear, however the reasons for using such a broad range are. DeBodt and Van Wassenhove (1983) have shown that various ranges of TBOs will lead to different costs even when forecast error is small. Specifically, smaller values of TBO lead to larger percentage cost increases. Studies by Blackburn and Millen (1980) suggest that a forecast horizon of 3 TBO is sufficient to minimize cost increases due to a small forecast horizon, but only for heuristic procedures.

Due to the sensitive nature of the Wagner-Whitten algorithm, Lundin and Morton (1975) suggest a forecast horizon of 5 TBO to ensure a cost performance that is within 1% of the "optimal" for an infinite horizon (Wemmerlöv and Whybark, 1984).

Callarman and Hamrin (1979), in one of the earliest studies of stochastic demand, compared the relative performance of six well-known heuristics (such as the EOQ, part-period, and Silver-Meal algorithms) under conditions of uncorrelated forecast errors and fixed lead times while using the coefficient of demand variation (s/m) and time between orders (TBO) as experimental factors. Their basic conclusion was that no single lot sizing rule was "best" under all conditions. They did rank the heuristics, however, with Wagner-Whitten coming out on top, followed closely by the EOQ, and ending up with Silver-Meal as one of the poorer performers. They also noted that total costs tended to increase with forecast error resulting in smaller differences in the relative performance of the heuristics. Callarman (1979) reaffirmed these results for an inventory model which, unlike the previous study, explicitly included stockouts. (From Tsado, 1985a, and Wemmerlöv and Whybark, 1984.)

Benton and Whybark (1982) confirmed the results of Callarman (1979) and Callarman and Hamrin (1979). Specifically, their study of three lot sizing techniques (using uncorrelated forecast errors and varying such system parameters as level of uncertainty), showed a negative correlation between relative heuristic performance (in terms of cost) and forecast error, i.e., as forecast error increased, the differences in cost performance of the three heuristics decreased. (From Wemmerlöv and Whybark, 1984.)

De Bodt and Wassenhove, in two separate studies, reported findings similar to those previously mentioned. Their first study (1981) examined the relative performance, both analytically and via simulation, of the Wagner-Whitten, Silver-Meal, and least unit cost algorithms. Using simulated constant demands injected with white noise and forecasted using exponential smoothing, they showed that cost differences were negligible even when the amount of forecast error was small. Although the assumptions on demand were rather restrictive, the simulation results bore out the analytical results regarding expected cost increases due to forecast error.

Their second study (De Bodt and Van Wassenhove, 1983a) used actual demand data but was also a simulation effort in that the forecast error was generated artificially. Their conclusions were essentially the same (i.e., Silver-Meal, part-period, least unit cost, and EOQ, adjusted to cover integral periods of demand, performed equally well), however they did state a preference for the basic EOQ model when used in a multi-stage environment. These results are interesting in that some of the operating conditions were different from those used in earlier research. Specifically, the authors assumed zero lead time and that the forecast error for the next period's demand was zero (implying zero probability of a stockout). These assumptions were made in order to make the analytical study tractable.

The following year, Wemmerlöv and Whybark (1984) presented a comprehensive study of 14 single-stage lot sizing techniques using demand uncertainty in the form of forecast errors introduced via simulation. The operating conditions are similar to those used by Benton and Whybark (1982), Callarman (1979), and Callarman and Hamrin (1979). However, they do incorporate non-zero lead times. Their most important results are quoted as follows:

"1. Relative cost performance is strongly affected by the introduction of forecast errors. The magnitude of these errors, however, is not significant.

2. The Wagner-Whitten procedure loses its position as the least cost rule (as in the deterministic demand model).

3. Only two rules, [Wagner-Whitten] and WMR3 [suggested by Wemmerlöv (1981)], remain on the list over the six best rules overall (from the list of best performers in the deterministic demand model).

4. The relative advantage of [Wagner-Whitten] compared to the other rules decreases.

5. The performance of the EOQ rule improves dramatically. This is, no doubt, due to the non-discrete character of this rule, leading to the ordering of a larger quantity than what is needed over an integer number of periods. In effect, then, the EOQ rule carries with it its own safety stock.

6. A wider choice of lot-sizing rules is available when compared to the `no uncertainty' case. Not only are there no differences, from a statistical standpoint, among the six best rules, but the cost penalties for several of the other heuristics are quite small. This can be contrasted to the case with no demand uncertainty, for which (Wagner-Whitten)... emerge[s] as being significantly better than the other rules."

They further point out that their simulation results seem to justify current industry practice. Specifically, Wagner-Whitten is not applied in industry (primarily due to complexity and "system nervousness" as shown in their study). The EOQ and Eisenhut algorithms, on the other hand, are widely used. Previous studies involving deterministic demand would lead one to believe this is bad practice. However, "if it is acknowledged that the `forecasts are always wrong', then current industry practice seems to be justified." In other words, the question of which lot sizing technique is the "best" becomes moot; a simple technique will probably suffice.

Tsado (1985a) concurs with the results of Wemmerlöv and Whybark (1984). However, he recognizes a serious limitation to their work and to the work of those that preceded them. All of these studies involved the use of simulated demand data and/or simulated forecast errors.

"While simulation is an important tool for analysing problems that requires (sic) complex mathematical solutions, it could lead to different results by different users, if there are differences in the way the data was simulated, or in the demand characteristics of the data. Moreover, simulations cannot always explain all the peculiarities of real life experience."

Additional problems with the previous works are:

1. Each study uses different versions of the part-period balance (see Heemsbergen, 1987).
2. There were contradictions in some of the initial assumptions (discussed previously).
3. All forecast errors were assumed to be unbiased. However, in actual practice forecasts may be biased.
4. Forecasting techniques (exponential smoothing, regression, etc.) were not used.

Tsado's (1985a) study therefore attempted to examine the possible interactions between demand pattern and lot size performance, lot-size technique and forecasting technique (or forecast parameters), and uncorrelated forecast errors and lot-size performance. His results follow:

"1. Forecast errors have tremendous influence on the performance of the heuristic policies even when these forecast errors are small.

2. With the exception of the incremental cost approach, the cost differences between a number of heuristic policies is small. This contrast(s) with the case of deterministic time varying demand function for which there

were significant differences between the performance of the heuristic policies.

3. The magnitude of the trend in demand and the type of forecasting technique used seem to have insignificant influence on performance...."

Tsado (1985a) hoped to validate the previous work on lot-sizing techniques (as well as compare his own heuristic developed specifically for stochastic demand), and, on the surface, it appears that he did. In the case of simulated data, he used (linear) exponential smoothing. He broadened his scope on the published data by including the use of Winter's seasonal forecasting model. He restricted his use to (linear) exponential smoothing once again for the actual demand data. His reasoning was that "these forecasting methods were (appropriate) because they provided reasonable forecasts." Unfortunately, Tsado limited his application of these forecasting techniques by using the entire demand history available to him to fit his forecast.

Industry, on the other hand, does not have this ability. In other words, forecasts are based on a limited demand history (if at all) and are then updated continuously over the "rolling horizon", i.e., from period to period. Tsado's methods therefore do not seem reasonable. What methods, then, are reasonable?

Makridakis, Andersen, Carbone, Fildes, Hibon, Lewandowski, Newton, Parzen, and Winkler (1982) established the following:

1. Knowledge of the underlying demand pattern of a time series does help in choosing a model.
2. Simple models seem to work well, especially when the basic series is changing or in the absence of prior knowledge as to the underlying structure of the demand pattern.
3. Under the conditions where simple models work well, the average of the forecasts from several simple models was superior to the forecast from a single model.

Flores and Whybark (1986), however, proposed a different method. A practitioner developed approach, this method, called focus forecasting, involves the selection of the one forecasting model which would have performed the best in the recent past to make the next forecast. As a result of continuous updating of all forecasting models, the choice of forecasting method may vary from time to time.

They compared both techniques (average vs. focus forecasting) using both synthetic (simulated) and empirical (actual) demand data. The method of averaging performed best on the synthetic data. More importantly, there was no significant difference in the relative performance of focus forecasting and forecast averaging when used on empirical data. The authors believe this is due to the higher mean average deviations (MADs) characteristic of actual demand. In other words, "empirical time series are far more difficult to forecast than the synthetic".

It is important to note that none of the seven forecasting techniques used for both focus forecasting and forecast averaging used any form of regression, exponential smoothing, Winter's method, or ARIMA modeling (although a simple moving average of 3 and 6 months was used). They did, however, compare the focus and averaging techniques with exponential smoothing (as a common basis of comparison) and observed that exponential smoothing generally outperformed both although the significance was not as great for the empirical demand data. It would therefore be interesting to apply focus forecasting to the more sophisticated exponential smoothing models.

Additionally, all of the aforementioned studies combined shortage costs with inventory holding and setup costs. (Some authors incorporated an arbitrary service level using a predetermined amount of safety stock.) Wemmerlöv and Whybark (1984) point out two approaches. One is to set stockout costs as a separate factor. However, they state that the results might not be meaningful when compared to other studies. The other, used by all of the studies cited, sets service levels via an appropriate amount of safety stock and quantifies only the inventory holding and setup costs.

A basic assumption for this method to be valid is that the "cost" of a stockout is the same for everyone. Another is that each heuristic employed performs the same for relative shortage costs as they do for relative inventory costs. These assumptions may not be valid, therefore it may be appropriate to look at these two types of costs separately.

Bookbinder and H'ng (1986) employed both forecasting methodology and stockout costs (separate from the standard inventory costs) in their study of rolling horizon production planning. Their main emphasis, however, was on the procedure for probabilistic production planning and not on the relative performance of the lot sizing rule employed within the procedure.

And finally, the baseline used in the previous studies on lot size algorithms to determine relative cost increases for each heuristic is questionable. Most of these works (including Wemmerlöv and Whybark, 1984) used the WagnerWhitten heuristic (i.e., given stochastic demand) as the baseline. Tsado (1985a) employed the EOQ "heuristic". But this is like trying to measure distance with a rubber ruler!

It is suggested that, in order to minimize the "error" inherent in such an approach, the optimal Wagner-Whitten solution given a-priori knowledge of the demand "history" should be used. The increase in cost due to the heuristic using forecast demand can then be thought of as the expected value of perfect information (EVPI). EVPI may be thought of as the maximum amount of money one would be willing to pay for perfect knowledge of the future. This approach should not only minimize the error in the design model, but should also be intuitively more appealing. (See Raiffa, 1968.)

Research Goals

There is a need for a study which forecasts empirical demand in the same manner in which the lot sizing algorithms are implemented, i.e., over a rolling horizon. For the purposes of this study, a system of focus forecasting is used.

Further, shortage costs need to be analyzed separately from inventory and setup costs since (1) shortages have a "variable" cost, and (2) the various algorithms may perform differently when shortages are treated as a separate entity.

Finally, validation of the stochastic heuristic presented by Tsado (1985a, b) is required.

CHAPTER III

LOT SIZE HEURISTICS

The lot size heuristics described are those developed for deterministic or discrete demand. As stated, there are three basic categories of lot size algorithms: EOQ-based, marginal cost-based, and target-based. The algorithms used in this study for each category are the standard EOQ, Silver-Meal, and part-period balance methods, respectively.

Also presented are Wagner and Whitten's (1958) dynamic programming method which is used as both an optimal baseline for cost comparison and as a separate lot size heuristic (when solved for forecast demand) and Tsado's (1985a, b) stochastic lot size heuristic. Although various refinements exist for all the heuristics listed, the simpler versions were used in the study.

Eisenhut

The part-period balance algorithm, hereinafter referred to as Eisenhut's lot size heuristic, determines the number of periods to order or produce by selecting that period for which holding cost most closely approximates the setup or ordering cost.

Using the example provided by Silver and Peterson (1985), let the setup cost = \$54, holding cost = \$0.40 per unit per period, and demand be given by D_i = {10, 62, 12, 130, 154, 129} for the first 6 periods. The algorithm yields

T=1: Holding = 0

T=2: Holding = D_2h = \$24.80 < \$52.00

T=3: Holding = \$24.80 + $2D_3h$ = \$34.40 < \$52.00

T=4: Holding = \$34.40 + $3D_4h$ = \$190.40 > \$54.00

Therefore since

$$|34.40 - 52.00| = 17.60 < |52.00 - 190.40| = 138.40$$

we produce for 3 integral periods.

EOQ

The economic order quantity, derived earlier, is non-optimal for the case of non-constant, or time-varying, demand. To be used as a heuristic in the case of stochastic demand, the average of the forecasted demand is used in the model.

Using the same example where D_i is a 6-period forecast, average demand is approximately 83 units. Therefore

$$Q^{*} = (2 \times 52.00 \times 83 \;/\; 0.40)^{\frac{1}{2}} = 147 \text{ units}$$

where Q^{*} is the "optimal" order quantity defined by the standard EOQ formula. Notice that the simple form of EOQ provides a non-integer time supply which, in effect, acts as an automatic safety stock (Tsado, 1985a).

<u>Silver-Meal</u>

Silver and Meal (1973) proposed a heuristic for time-varying, deterministic demand which uses the concept of marginal cost, i.e., it attempts to minimize total relevant costs per unit time (a quantity which we will refer to as TRCUT). Expressed as a function of time,

$$\mathrm{TRCUT}(T) = [A + {}_{T} \; ((t-1) \; D_t \; h)] \;/\; T$$

where A is the setup cost and ${}_{T} \; ((t-1) \; D_t \; h)$ is the total carrying cost to the end of period T. Selection of the "optimal" number of periods to include in the replenishment occurs when TRCUT(T+1) > TRCUT(T). Using our previous example:

T=1: TRCUT(1) = 54.00/1 = $54.00

T=2: TRCUT(2) = (54.00 + 1 x 62 x 0.04) / 2 = 39.40

T=3: TRCUT(3) = (78.80 + 2 x 12 x 0.04) / 3 = 29.47

T=4: TRCUT(3) = (88.40 + 3 x 130 x .04) / 4 = 61.10

and we select a replenishment quantity which will cover 3 periods.

Tsado

Tsado's (1985a) stochastic heuristic is primarily a modification of the EOQ which incorporates the idea of minimizing total relevant costs for a given replenishment cycle while keeping track of previous costs. As this method is generally unknown, more will be said regarding its derivation.

The assumptions used in the derivation are (1) no shortages are allowed, (2) demand for the next period is known with certainty, (3) all other periods are forecast, (4) a replenishment occurs in period t if demand cannot be satisfied for period t+1, and (5) demand is assumed to be steady and continuous. The first two assumptions are basically equivalent and neither is used in this research, i.e.,, we allow shortages.

Tsado (1985a) first derives an equation for the expected increase in stockholding costs, St_c, given that (1) lead time is zero, (2) replenishment occurs instantaneously, and (3) stock at the end of the replenishment interval is zero. Specifically,

$$St_c = h\ D\ L^2 / 2$$

where h is the inventory holding cost in \$/unit/period, D is the rate of demand (continuous), and L is the length of the replenishment interval. Note that, although the formula is derived for the continuous model, the heuristic is applied discretely, i.e., to periodic demand.

He then shows, given $L = T - t$ (since we wish to satisfy demand up to the horizon, T), that

$$St_C = L^2 D h / 2 = (T - t)^2 D h/2$$

where St_C and L are as previously defined, D is the current forecast of demand or its average, h is as previously defined, T is the last period in the forecast horizon, and t is the period of the present setup.

This implies that total relevant costs at time T may be written as

$$\begin{aligned} TRCUT(T) &= [\, Z_t + (T - t)^2 D h/2 + S \,] / T \\ &= (Z_t + S)/T + [\, T - 2t + t^2/T \,] D h/2 \end{aligned}$$

where Z_t is the total inventory cost (holding and setup) up to time t and S is the fixed cost of the setup.

Taking the derivative with respect to T,

$$dTRCUT(T)/dT = -(Z_t + S)/T^2 + (1 - t^2/T^2) D h/2$$

which set to zero yields

$$T = [\ t^2 + 2(Z_t + S)/Dh\ ]^{\frac{1}{2}}$$

Since $L = T - t$ and the replenishment quantity, Q, is equal to the average forecast of demand, D, times the replenishment interval, L, Tsado's lot size formula becomes

$$Q = DL = D\,(T-t) = DT - Dt = -(Dt) + DT$$

$$= (-Dt) + [\ (Dt)^2 + (2D\,(Z_t + S))\ /\ h)^{\frac{1}{2}}$$

When t=0, this equation reduces to the simple EOQ formula, therefore the first setup for our example will be identical to that obtained previously.

Wagner-Whitten

Wagner and Whitten's (1958) algorithm is a dynamic program which provides an optimal solution to the discrete, time-varying lot size problem. When used as a heuristic for the stochastic demand model, the algorithm computes the "optimal" solution over the forecast horizon using the forecasted demand. Using our example, the Wagner-Whitten procedure and solution are shown in Table 1.

The column signifies the period where a setup occurs and the row gives the current period we are looking at.

N	1	2	3	4	5	6
1	52.00*					
2	52.00 24.80 76.80*	52.00 52.00 104.00				
3	76.80 9.60 88.40*	104.00 4.80 108.80	76.80 52.00 128.80			
4	88.40 156.00 244.40	113.60 104.00 217.60	128.80 52.00 180.80	88.40 52.00 140.40*		
5				140.40 61.60 202.00	140.40 52.00 192.40*	
6					192.40 51.60 244.00*	192.4 52.00 244.40

Table 1. Wagner-Whitten Procedure

The figure in row 1 and column 1, referred to as (1,1), gives the total cost in period 1, i.e., the cost of the setup.

Cost (2,1) gives us the total cost if we produce enough in period 1 to cover periods 1 and 2, whereas (2,2) is the total cost if we produce in both periods. The first number at each point in the matrix gives the total inventory cost (setup and holding) from the previous period. The second number provides the inventory holding cost of the current period (if we had produced in the previous setup for that period's demand) or the setup cost as required.

The asterisk shows the "optimal" policy for the current period, and, except for the policy where we "test" for a setup (which is given on the diagonal), that cost is carried over to the next period we wish to look at (every (i,j) "period" where j < i).

The Wagner-Whitten theorem states that, once the optimal policy occurs in column j, calculations may be discontinued for any column i where i < j.

In general, a cost C(i,j), means that we set up in period j to produce demands for periods j, j+1,..., i, and that the demands for periods 1, 2,..., j-1 are produced by an optimal policy.

Unlike the previous heuristics, the Wagner-Whitten algorithm must be used over the entire forecast (time-rolling) horizon, but, like the others, only the first period's decision is implemented. Cost calculations are carried out in the same manner as in the other heuristics.

The "optimal" Wagner-Whitten solution is read backwards through the matrix using the "starred" costs as a guide. For our example, we show setups in periods 1, 4, and 5 and would produce in the first period for periods 1, 2, and 3.

Note that optimality of the Wagner-Whitten procedure is no longer guaranteed since the assumptions of deterministic demand and zero demand after period T, where T is the planning horizon, are violated.

CHAPTER IV

THE FORECAST MODEL

Time series analysis involves developing forecasts of a variable entirely from its past history. These techniques generally model the variable in such a way that past patterns in the data series are used to help modify the mean and thereby predict future values. Although past performance is no guarantee of future performance, time series methods are generally successful in statistically stable conditions, for short-term forecasts where there is insufficient time for substantial change barring catastrophes (as in our current study), as a base forecast for judgemental models, and for screening data in order to better understand the variable being forecasted (Barron and Targett, 1985).

Introduction

Jenkins (1979) describes five classes of time series models. These are:

1. univariate models in which a single variable is forecast from its own past history,

2. transfer function models which add inputs from other variables,

3. intervention models which represent unusual events such as strikes, etc.,

4. multivariate stochastic models which represent several series with mutual interaction, and

5. multivariate transfer function models which relate several output variables to several input variables in which a relationship exists.

Univariate models, although of an elemental nature, are important from a forecasting viewpoint for several reasons. First, they may be the only model which is the only practical approach based on the magnitude of the problem. Second, it may be impossible to find, or there may not exist, variables related to the one being forecast. Third, when multivariate models exist, the univariate model may be used as a baseline to measure the other's performance. And finally, the presence of large residuals (the difference between actual values and the "stationary mean") may correspond to strikes, faulty data, etc. and therefore act as a tool to screen data. In spite of these points, however, it must be recognized that univariate models are generally valid for short-term forecasts only (Ibid.). As all of the studies mentioned in Chapter II utilized univariate forecasting methodology, this discussion will be restricted to procedures in this area.

Univariate models are classified by Barron and Targett (1985) according to the type of series to which they can be applied. These are:

1. stationary (random variation about a mean or a series which may be modeled as a stochastic "random walk"),

2. trending (a consistent movement either upwards or downwards in the series),

3. seasonal/cyclical (a series which exhibits a pattern over a number of time periods where seasonal implies a period of a year or less and cyclical refers to a pattern greater than one year), and

4. seasonal and/or cyclical with a trend (a complex of seasonal and/or cyclical patterns and trends).

The last three classifications may be grouped under the heading of non-stationary time series. Johnson and Montgomery (1976) state that the basic goal in any univariate time series method is to reduce the residuals, or error, to a normally distributed random variable with mean zero and constant variance (also known as "white noise"). In other words we seek a stationary model from a non-stationary time series. (See Hoel, Port, and Stone, 1972.)

There are two general types of time series forecast methods, those involving smoothing techniques and those involving autoregressive parameters, generally referred to as ARMA (p,q) models. Johnson and Montgomery (1976) suggest that ARMA models should be considered only when there exists a sufficient amount of demand history for analysis, typically around 36 periods or more. Since large amounts of demand history from the same environment may not always be available and previous studies have not utilized ARMA models, ARMA models were not considered for use in the current study.

Further, since lot sizing is performed on a rolling horizon, forecasting should be performed on the same basis. Therefore, we will restrict ourselves to exponential smoothing models when applied to the concept of focus forecasting.

Exponential Smoothing

Smoothing techniques (or models) replace the original time series by a "smoothed" one, i.e., one produced from statistical or weighted averages of values from the original series in an attempt to reduce or discount the random fluctuations or variance. Generally, the last smoothed value(s) provide(s) the forecast for all future time periods in the (rolling) forecast horizon.

Simple Exponential Smoothing Model

The simplest case is, of course, when the time series is already stationary, i.e., it may be represented by

$$x_t = m + e_t$$

where m (or mu) is the statistical mean of the time series and e_t is the error or difference between the mean and the actual value of the data point. Two techniques which deal with such stationary models are moving averages (not discussed) and simple exponential smoothing.

Exponential smoothing assumes that recent data is more important than old data; a concept which is rather intuitively appealing. Then, based on the relative value attached to the significance of the residuals, it computes a smoothed "average" of the data. Specifically, the model states

$$S_t = (1 - a)\ S_{t-1} + a\ x_t$$

where S_t is the new smoothed value at time t, S_{t-1} is the old smoothed value at time t-1, x_t is the most recent actual value, and a (or alpha) is a weight chosen by the forecaster such that $0 < a < 1$. Obviously, the larger the value of alpha the more weight will be attached to the most recent data point.

To see this, one merely needs to expand the equation for all "N" which yields

$$S_t = a\ x_t + a\ (1-a)\ x_{t-1} + a\ (1-a)^2\ x_{t-2} + \ldots$$

where the weights given to the data points from the most recent to the most distant are a, a (1-a), a $(1-a)^2$, and so forth (Barron and Targett, 1985). Since both a and (1-a) are less than one, the weights are decreasing monotonically with time.

Silver and Peterson (1985) rewrite the exponential smoothing model to obtain

$$S_t = S_{t-1} + a\ (x(t) - S_{t-1}) = S_{t-1} + a\ e_t$$

where all variables are as previously defined. This implies the new forecast value is equal to the old forecast value minus a fraction of the most recent error. In other words, the exponential smoothing model assumes that a portion of the last forecast error, namely (1-a) is due to some random fluctuation and the other portion, namely alpha, is due to some real shift in the value of the estimate. In practice, the value of alpha usually ranges between 0.1 and 0.4 (Ibid.).

Holt's Exponential Smoothing Model

Now consider time series which are initially non-stationary but which can be made stationary by differencing. By differencing we mean

$$\text{DEL } S_t = S_t - S_{t-d}$$

where DEL is the differencing operator and d is the period of differencing. For a strictly trending time series, a difference of d=1 will yield a stationary time series.

To see this, one must first examine the statistical significance of trending and seasonal data. When a time series trends, the values between successive data points are highly correlated. (Since the time series is correlated with itself, a more appropriate term is "autocorrelated".) The same is true for seasonal time series where the autocorrelation occurs at lag d, i.e., for time series values S_t and S_{t-d}. The differencing operator therefore yields white noise, i.e., the residuals are normally distributed with zero mean and constant variance (Jenkins, 1979). As mentioned earlier, the objective of all time series analyses is to fit a model such that the residuals yield white noise (Johnson and Montgomery, 1976).

Due to the nature of how the forecasting methodology was implemented, exponential smoothing models which account for seasonality were ignored. Trend, however, is accounted for through the use of Holt's exponential smoothing model. (Linear regression may also be used but was not employed in this study.)

A strictly trending (linear) time series will take the form

$$x_t = m + \beta t + e_t$$

where βt defines a linear trend (as a function of t) with slope β. Other trends are possible. However, our discussion is limited to linear trends. Successfully differencing a time series more than once for trend is a good indication the trend is non-linear (Ibid.).

Let the trend at time t be given by $T_t = S_t - S_{t-1}$. Since S_t is a random variable, T_t is also a random variable. Therefore, using the same logic as simple exponential smoothing, we can smooth the trend by the following:

$$T_t = (1 - g)\ T_{t-1} + g\ (x_t - x_{t-1}))$$

i.e., the smoothed trend is equal to a portion of the previous smoothed trend plus a portion of the most recently observed trend. The selection of g (or gamma) is made in the same manner as alpha.

Using this estimate, we can modify S_{t-1} in the simple exponential smoothing model to obtain

$$S_t = (1 - a)\ (S_{t-1} + T_{t-1}) + a\ x_t$$

or more generally

$$F_{t+i} = S_t + i\ T_t$$

where F_{t+i} is the forecast for the t+i'th period (Barron and Targett, 1985)

<u>Focus Forecasting</u>

Flores and Whybark (1986) studied two forecasting systems, "one recommended by practitioners for use in inventory management, and the other the result of an international forecasting competition among academics." These are the methods of focus forecasting and forecast averaging, respectively.

Although this topic was touched upon briefly in the literature review, we would like to say a little more regarding the aforementioned study and our proposed extension.

The forecast procedures used in the comparison were very simplistic, e.g., "the forecast for the next month is the actual demand for the same month last year.... [or] ...is one-sixth of the total actual demand for the last six months (a two-quarter moving average)." Another, slightly convoluted approach was "if the demand in the last six months is more than 2.4 times the demand for the six months preceding that, the forecast for the next month is one-third of the demand for the same three month period last year (i.e., we are starting into the downside of a seasonal swing)."

The focus and averaging techniques were then compared to each other and, most importantly, to exponential smoothing, i.e., exponential smoothing provided the "baseline" for comparison.

Although averaging performed better than focus forecasting on the simulated data (there was no statistical difference for the empirical data), neither procedure performed better than exponential smoothing. In fact, exponential smoothing was significantly better than either of the other two procedures.

Exponential smoothing would then seem to be the obvious choice. The next question, however, is the selection of alpha and gamma, i.e., the forecast parameters. Past studies have "fit" the parameters over the entire demand history of each empirical data set (when empirical data were used). Industry, of course, doesn't have this type of clairvoyance; they would have to take an educated guess given a limited demand history and monitor the forecast model to make appropriate changes when necessary. But, since this study was "automated", we did not have this "luxury" either.

It therefore makes sense to either (1) average the exponential smoothing forecasts from varying parameter levels or (2) use the focus forecasting approach. We selected the focus forecasting approach as it seems to be the most appealing (intuitively). The idea is to keep track of the mean absolute deviation and bias of a set of exponentially smoothed forecasts and select the one best forecast for the next planning horizon.

Silver and Peterson (1985), however, argue that changing the smoothing constants (what they refer to as "adaptive" smoothing), while having considerable intuitive appeal, is "not necessarily better than regular, non-adaptive smoothing." (See Ekern, 1981; Flowers, 1980; and Gardner and Dannenbring (1980)) Specifically, they feel the resulting forecasts would be excessively "nervous".

Fortunately, the lot sizing problem only requires use of an extended forecast about every "TBO" periods. For our purposes, the focus, or adaptive, approach should be quite reasonable. In fact, comparisons of the mean absolute deviation (MAD) for the adaptive procedure to the MADs of each individual, static procedure (tested during program development) were quite favorable and tend to support this position.

Separate research regarding the relative merit of focus or "adaptive" and averaged exponential smoothing techniques (as used in automatic forecasting) is probably warranted.

CHAPTER V

THE EXPERIMENT

This chapter constitutes the bulk of this research and is divided as follows: Sample Data, Assumptions, Performance Criteria, Computer Model, Experimental Design, Results, and Analysis. Concluding remarks are contained in Chapter VI.

Sample Data

Data was obtained from two separate industrial sources. The first group originally contained 500 data sets consisting of 52 weekly periods, however only 207 of these proved suitable for our purposes. Specifically, all data sets which contained an alphanumeric or zeroes were discarded. The second group was very limited at 5 data sets, however each data set consisted of 78 (monthly) periods.

From the first group of 207, 36 were selected randomly for the study. They were then classified according to the coefficient of variation and data type.

The variability of each data set was determined to be either low ($0 < s/m < 0.5$), medium ($0.5 < s/m < 1.0$), or high ($s/m > 1.0$), where s (or sigma) is the standard deviation. Selection of the "cut-offs" were arbitrary.

Data type consisted of two classifications: linear and non-linear. The reason for this was two-fold. First, a relatively small number of data sets were selected for the study. Second, the forecast model used simple exponential smoothing as well as Holt's exponential smoothing model for a linear trend, i.e., it wasn't "designed" to handle a non-linear demand pattern. It was therefore necessary to account for the possibility the forecast model would perform worse for the non-linear case.

An ARIMA "identify" was performed on each data set using the Statistical Analysis System (SAS) ((c) 1985 by SAS Institute Inc.) in order to determine which demand patterns could not be considered level, i.e., as white noise. A second "identify" using a differencing of 1 determined which demand patterns could be considered non-linear.

A complete listing of the 36 demand patterns in the first group is given in Appendix A, however we will discuss a few selected patterns here.

Figure 1 shows a plot of the first data set. Although the demand series is generally linear with a relatively small variance, large outliers occurring at periods 14 and 16 "inflate" the coefficient of variation to 1.49. Outliers

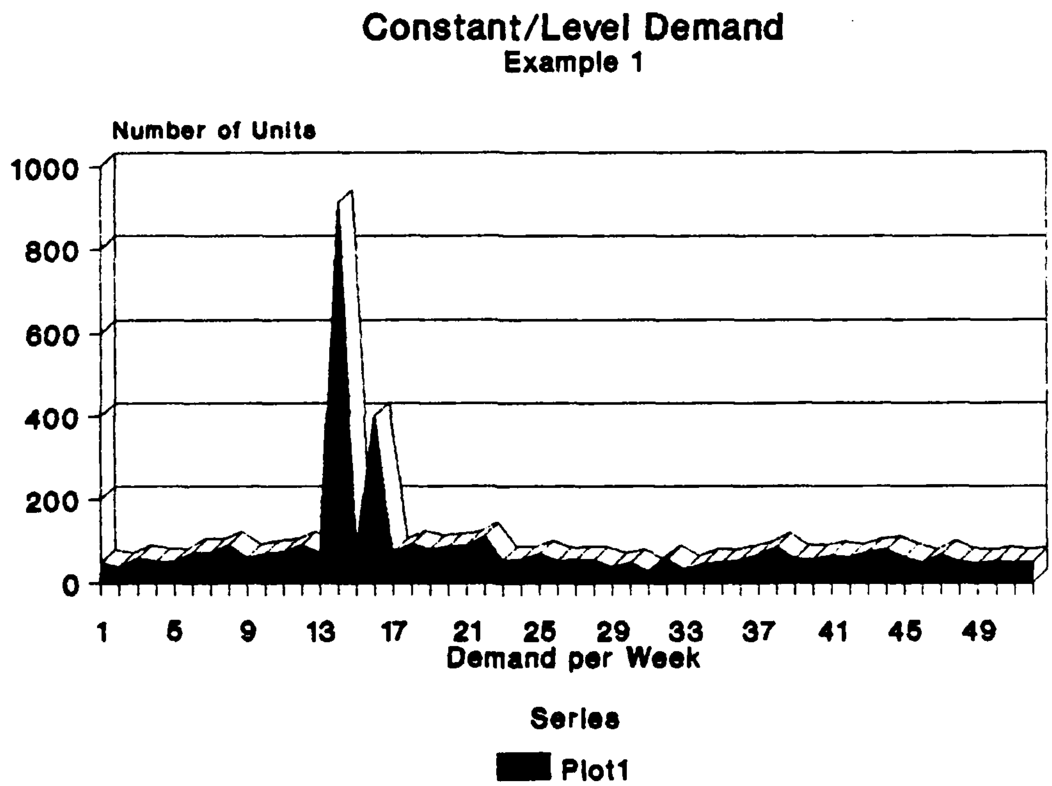

Constant/Level Demand
Example 1
Number of Units
1000
800
600
400
200
0
1
5
9
13
17
21
25
29
33
37
41
45
49
Demand per Week
Series
Plot1

Figure 1

such as these posed somewhat of a problem for the automatic forecast model; a procedure discounting such outliers was developed and will be discussed at a later point in this chapter.

The demand series depicted in Figure 2 also constitutes white noise, however "spikes" occur at periods 2, 16, 32, 33, and 46. If one considers periods 32 and 33 to be "split", then the spikes occur about 1 every 15 cycles. Like the previous demand series, these spikes inflate the coefficient of variation to about 1.68.

Figure 3 on the other hand shows no significant spiking when compared to the general variability of the data set. This demand pattern qualified as white noise and showed a moderate coefficient of variation of about 0.49.

A demand series showing a slight downward trend (after an initial upswing) and moderate variance (coefficient of variation of approximately 0.33) is shown in Figure 4. Figure 5 shows a demand series with a definite drop in demand in period 8 followed by an upward trend. Coefficient of variation for this series is slightly higher as a result (about 0.53). Both series are considered linear (non-constant).

Non-linear demand sets are given in Figures 6 and 7. Figure 6 shows a rough "concave" pattern which is somewhat obscured in spite of the relatively low coefficient of variation (0.35). The non-linear pattern of Figure 7, on

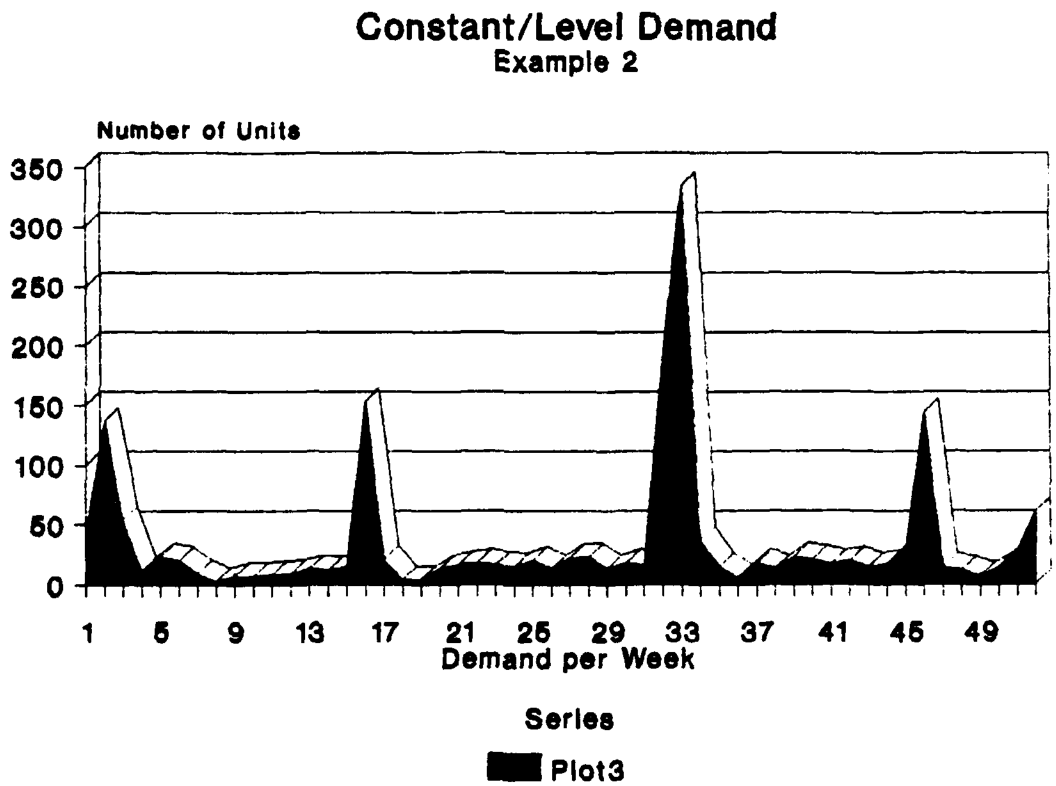

Constant/Level Demand
Example 2
Number of Units
350
300
250
200
150
100
50
0
1
5
9
13
17
21
25
29
33
37
41
45
49
Demand per Week
Series
Plot3

Figure 2

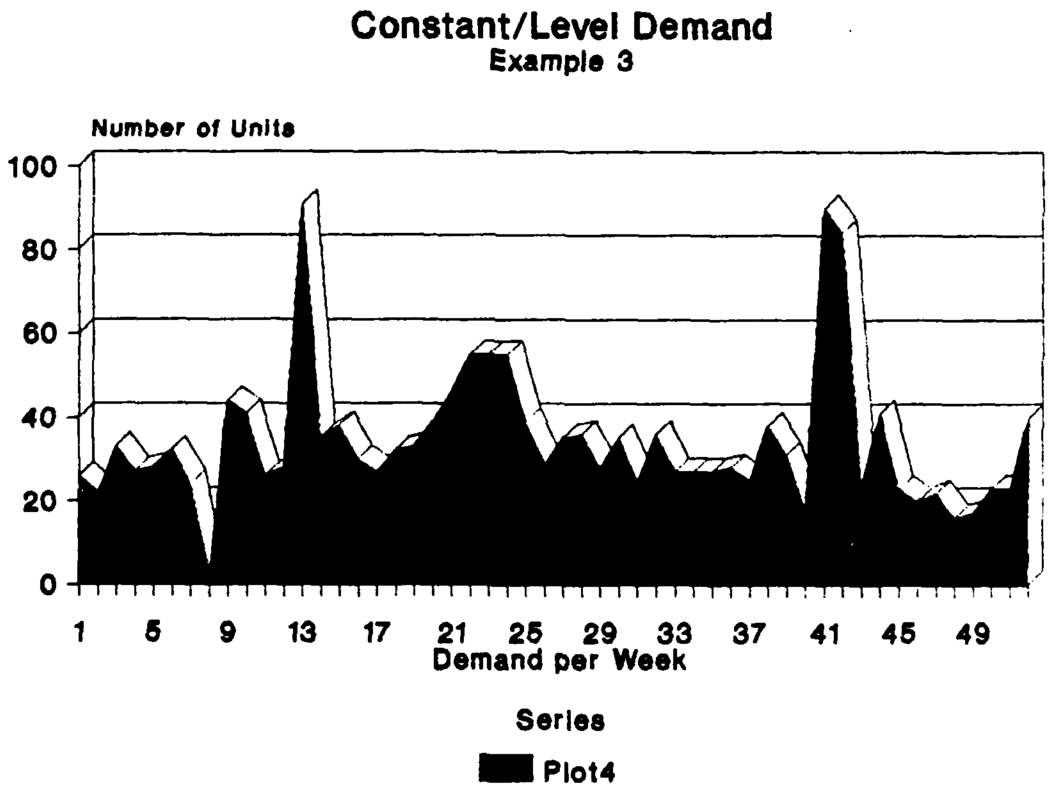

Constant/Level Demand
Example 3
Number of Units
100
80
60
40
20
0
1
5
9
13
17
21
25
29
33
37
41
45
49
Demand per Week
Series
Plot4

Figure 3

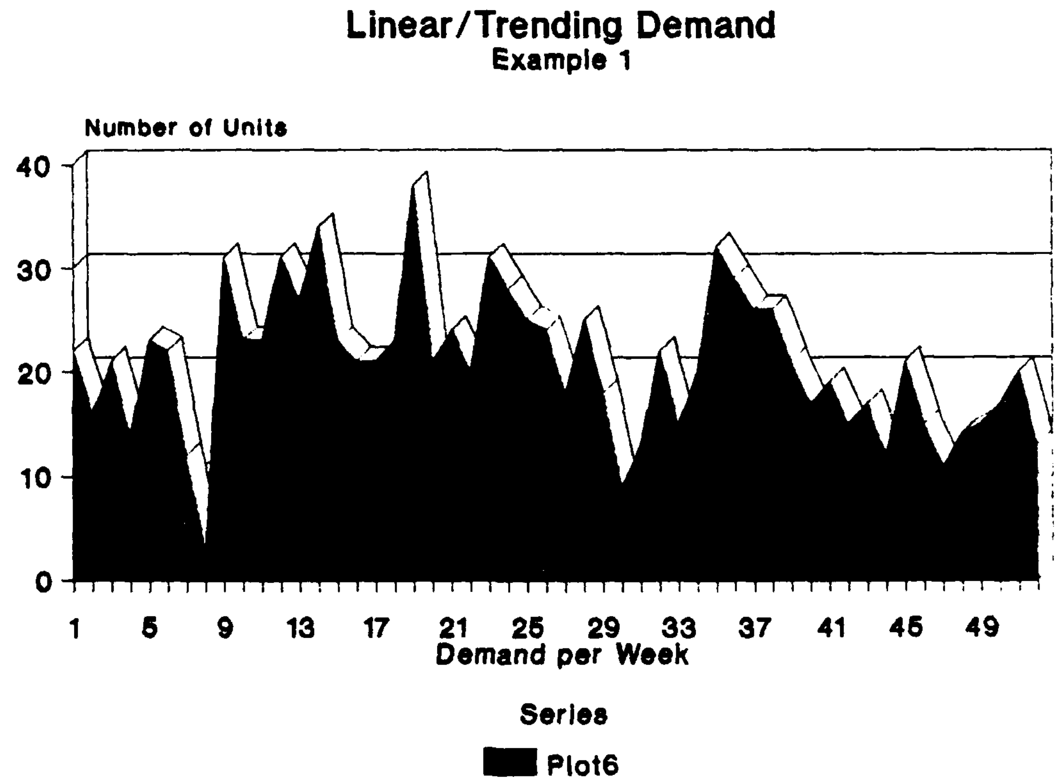

Linear/Trending Demand
Example 1
Number of Units
40
30
20
10
0
1
5
9
13
17
21
25
29
33
37
41
45
49
Demand per Week
Series
Plot6

Figure 4

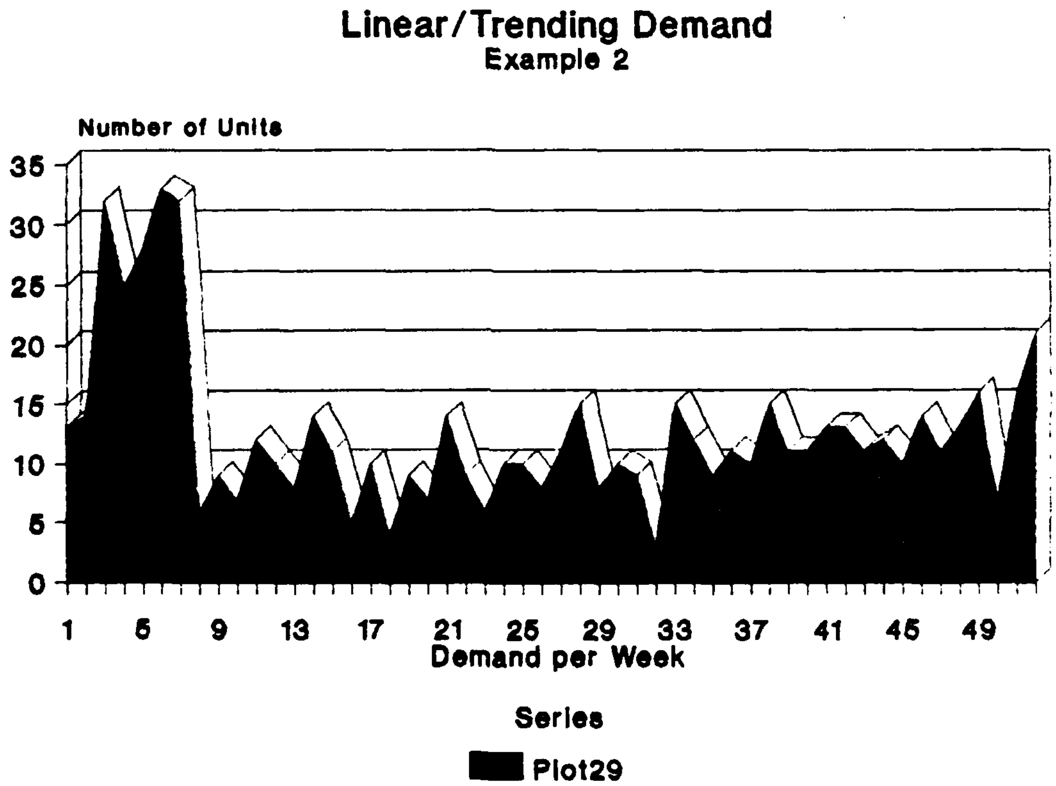

Linear/Trending Demand
Example 2
Number of Units
35
30
25
20
15
10
5
0
1
5
9
13
17
21
25
29
33
37
41
45
49
Demand per Week
Series
Plot29

Figure 5

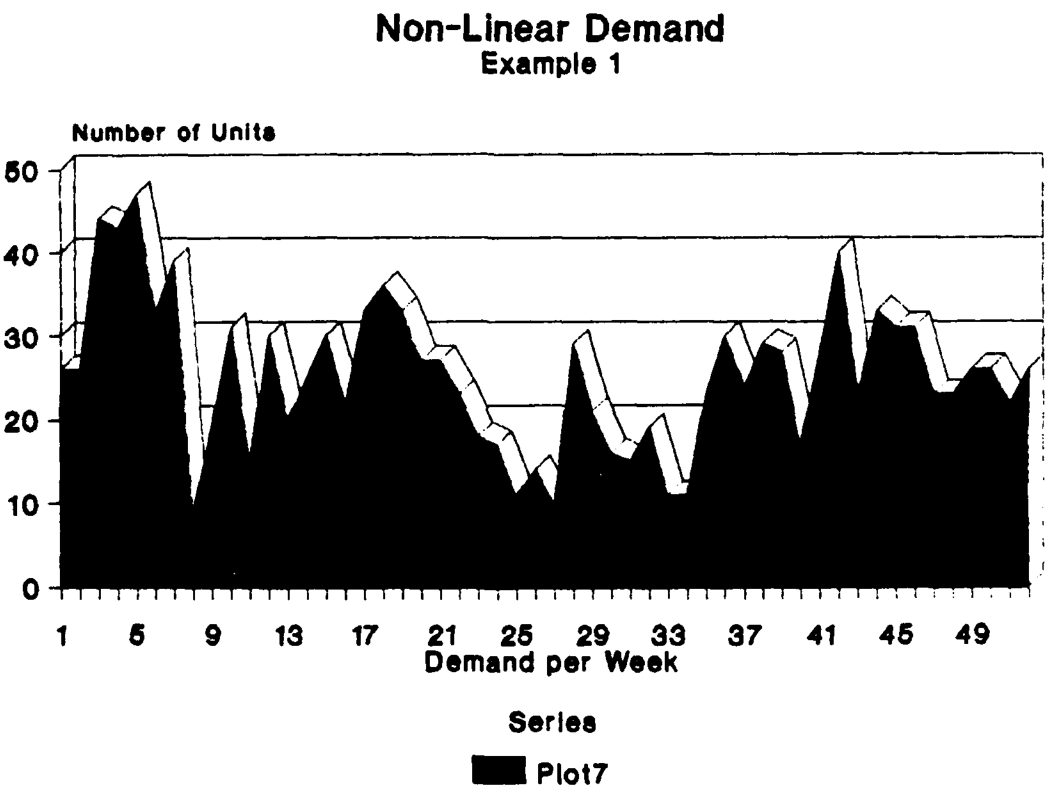

Non-Linear Demand
Example 1
Number of Units
50
40
30
20
10
0
1
5
9
13
17
21
25
29
33
37
41
45
49
Demand per Week
Series
Plot7

Figure 6

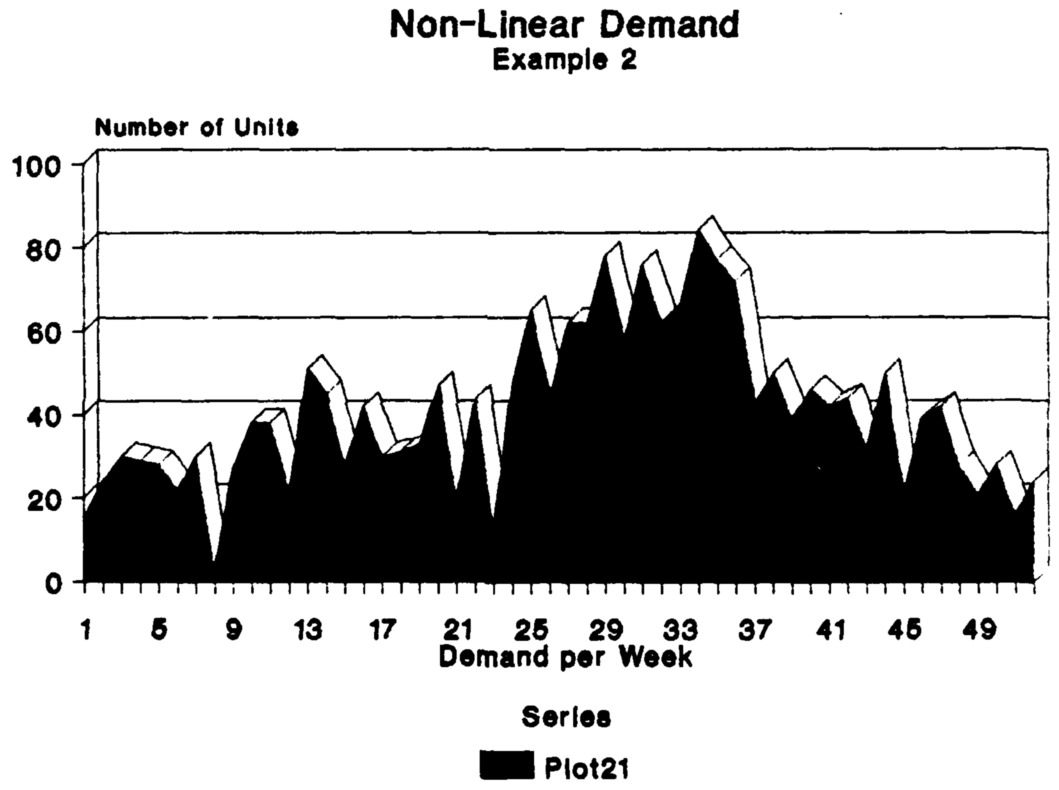

Non-Linear Demand
Example 2
Number of Units
100
80
60
40
20
0
1
5
9
13
17
21
25
29
33
37
41
45
49
Demand per Week
Series
Plot21

Figure 7

the other hand, is clearly convex and could very well be seasonal (although we can't be sure due to the limited history). The coefficient of variation for this set is a slightly higher 0.46.

Table 2 shows the exact break-out of the 36 demand sets in this group.

	Structure	
Coef of Var	Linear	Non-Linear
Low	12	8
Medium	6	5
High	5	0

Table 2. Data Classification -- Group 1

The data in the second group is given in Appendix B. Due to the limited number of data sets in this group, they were not classified by data type or degree of variation. It should be noted, however, that significantly more variation in structure can exist for these longer demand sets as they span a period of over 5 years.

Assumptions

Assumptions used to develop the single-stage, production lot size problem are similar to those employed by other research and are as follows:

1. Demand is probabilistic and is forecast using a limited amount of prior history.

2. A fixed cost is incurred for each setup.

3. The inventory holding cost is a function of the amount of inventory on hand at the end of a given period.

4. Production lead time is zero (i.e., we have enough inventory at the end of a production period to meet that period's demand).

5. All demands are met at the end of each period.

6. There is no safety stock except that inherent in a particular lot size heuristic.

7. Back orders are allowed.

8. There is no monetary penalty for shortages in the cost calculations (i.e., shortages are handled as a separate criteria).

9. Demand for the next period is not known with certainty.

10. An updated forecast is available for any period.

Performance Criteria

There are three types of criteria (dependent variables) of interest in this study. These are cost, number of stockouts, and the amount short per stockout.

Relative Cost

Previous studies have used the Wagner-Whitten procedure when used as a heuristic as the baseline for cost comparisons. Unfortunately, the Wagner-Whitten procedure is suboptimal in the case of a rolling horizon and probabilistic demand.

Arguments for the use of the Wagner-Whitten heuristic as the baseline are:

1. Wagner-Whitten is the baseline used for the deterministic case.

2. It's not known before hand which rule will outperform the others.

3. Use of the Wagner-Whitten "heuristic" will make the study more easily comparable to previous works.

We feel these reasons do not justify the use of one heuristic as a basis of comparison. It's true that we do not know what the optimal cost of a probabilistic lot size problem will be until the demands have already been satisfied, i.e., we don't know what our future demands will be. However, by comparing the cost obtained through the use of a heuristic (when demand is considered stochastic) with the optimal cost obtained by Wagner-Whitten over the entire demand "history" (when considered deterministic), we obtain a true, fixed reference for comparison.

The key is the interpretation of the cost comparison. Specifically, this difference in cost may be thought of as the maximum amount of money we would be willing to pay for perfect knowledge of our future demand (referred to as the expected value of perfect information or EVPI). (See Raiffa, 1968.)

Number of Stockouts

Wemmerlöv and Whybark (1984), Tsado (1985a), and others arbitrarily set service levels in order to handle the question of stockouts. By service level, we mean that there exists enough safety stock to assure demands are met at least percent of the time. Generally, levels between 90 and 99.999 percent have been chosen. As a result, the stockout question is largely ignored.

Since we assume that stockouts have a "variable" cost, i.e., the cost of a stockout to one organization may be quite less than that perceived by another, setting an arbitrary service level may not be appropriate. Further, by pre-determining a service level, the effects of a lot size algorithm on inventory (holding and setup) costs and stockout costs may be confounded.

In a manner similar to that employed by Bookbinder and H'ng (1986), we chose to "count" the number of times a lot size heuristic produced a stockout. Obviously, this number will vary according to the TBO level, therefore we chose to compute the stockout "cost" as the number of times a stockout occurred expressed as a percentage of the number of replenishments made.

For example, given a 52 period demand "history" with a TBO level of 2, then 5 stockouts out of 26 replenishments (approximately) will yield a stockout "cost" of 0.1923, i.e., about 19.23% of the replenishments made experienced a stockout. For a TBO of 6, 5 stockouts would imply a "cost" of 57.69%.

Percent Short per Stockout

Another factor in the stockout question is the amount of shortage when a stockout occurs. The average number short per stockout is therefore an important "cost" consideration, however, an average shortage of N units doesn't tell us much.

There are two ways of handling this problem. One is to express the shortage as a percentage of average demand, another is to express it as a percentage of the demand for the period in which we were short. We chose the later.

Justification for our selection is as follows. Consider an average demand of 500 units. If we were to have forecast a demand of 550 units where actual demand was 600 units, then our percentage short is only 8.3% of the actual demand. If we had used average demand, we would have shown a shortage of 10%. Now assume an average demand of 50 units. Similarly, assume a forecasted demand of 100 units and an actual demand of 150 units. But now we show a shortage of 33.3% of actual demand and a misleading 100% of average demand.

In both cases the forecast was 50 units greater than average demand, and actual demand was 50 units greater than forecasted demand. Obviously, shortage "cost" expressed as a percentage of actual demand is a more accurate estimate of the true "cost" associated with a shortage.

Computer Model

Although not a simulation study, a computer model was used to generate forecasts, compute production policies via the various lot size heuristics (including the optimal Wagner-Whitten cost), and to compute the costs associated with each policy. This section discusses the issues of program development and validation.

Program Development

Both the forecasting procedure and lot size procedure were automated via a program written in MICROSOFT QuickBASIC (R) and run on an IBM XT (R) compatible microcomputer. The program listing is given in Appendix C.

For purposes of clarity, this section is further subdivided into 2 groups. The first discusses the forecast algorithm; the second addresses the lot size procedure.

The Forecast Procedure. The complete forecast is generated over the entire demand history of each data set (on a rolling horizon basis) prior to implementation of the lot size procedure. Estimates of level demand and trend (when Holt's exponential smoothing model is used) are stored in memory. Although the forecast for each period is used in the lot size procedure, extended forecasts are only developed when required by the particular lot size heuristic employed.

To provide a compact computer algorithm, the simple exponential smoothing procedure was incorporated into Holt's procedure by setting the trend parameter, g, to zero.

Focusing is carried out by keeping track of each individual or single forecast's mean absolute deviation and smoothed error tracking signal (bias). (Estimates of the MAD are also exponentially smoothed.) The forecast with the best current MAD is selected for the focused model if the bias is within acceptable limits, specifically between -0.8 and 0.3.

Silver and Peterson (1985) argue that a negatively biased forecast, i.e., where forecast exceeds demand, is preferable to a positively biased forecast, i.e., where demand exceeds the forecast, since being a few items overstock is preferable to consistently being short (causing too many premature setups).

Wemmerlöv and Whybark (1984) specifically avoid the use of biased forecasts by adjusting the average actual demand per period to equal the average forecast demand per period. While easily done for simulated demand data, it's generally not appropriate for empirical demand forecast on a rolling horizon basis.

Research by Lee, Adam, and Ebert (1987) show that "bias is the only measure that satisfactorily reflects inventory carrying cost... [and] only bias displays any reasonable association with the shortage cost and shortage units...."

Since carrying cost is caused by over forecasting (what they refer to a positive bias) and shortage costs are caused by under forecasting (referred to as negative bias), the use of an unbiased forecast (as used by Wemmerlöv and Whybark (1984)) might seem reasonable. The research by Lee, et al. (1987), however, shows that "the structures of these two component costs may not be symmetrical about the zero bias level." Unfortunately, they do not provide guidelines as to what the nominal bias levels may be.

The specific bias levels used in the forecast model were determined in conjunction with an outlier discounting criterion. An example data set which exhibited a steep downward trend due to large upward spikes (outliers) was used. The steep downward trend was "leveled" somewhat by discounting the outliers (more on this in a moment) and then varying the bias criteria in an effort to eliminate a large series of zero forecasts caused by the initial "trend". (The data set used is shown in Figure 1.)

Outliers were discounted by keeping track of the average demand and standard deviation of the series at each point in the forecast "cycle". If an outlier exceeded 4 standard deviations, the actual demand was reduced to the mean plus 4 standard deviations for forecast purposes. This provided a stabilizing influence on the forecast which otherwise would have to have been provided by human intervention. On the downside, the forecast model would lag slightly behind a true shift in the mean of the demand series. (This type of lag is a standard "penalty" for exponentially smoothed forecast procedures.)

The Lot Size Procedure. Other than the Wagner-Whitten algorithm, the other heuristics are simple to use and will not be discussed here (please refer to Appendix C for more information). Our discussion will be limited to that part of the procedure which determines our production policy.

Research on lot size procedures has been performed by Silver (1978), Askin (1981), Bookbinder and Tan (1983), and Bookbinder and H'ng (1986). Our procedure, while developed prior to our knowledge of the previous works, is similar to that suggested by Bookbinder and Tan.

Our procedure is as follows:

1. Use a focus forecast from simple exponential smoothing and exponential smoothing with trend models for demands over the rolling horizon.

2. Treat the forecast demands as deterministic and employ a specific lot size heuristic.

3. If on-hand inventory is positive, the amount produced will be the amount obtained from the lot size heuristic minus the on-hand inventory.

4. If on-hand inventory is negative, i.e., a stockout has occurred, the amount produced will be the amount obtained from the lot size heuristic plus the amount backordered.

5. Each period, the on-hand inventory is compared to

the forecast for the next period. If our forecast exceeds our inventory position, we schedule a setup for the next period, otherwise we continue.

6. When the next period's demand is realized, we either meet demand or we're short. If a shortage occurs, a setup is scheduled for the next period, otherwise we look at next period's forecast (Step 5).

7. We develop an extended forecast only when a setup is scheduled.

8. Continue this procedure until we exhaust all available demand data.

9. Discount the inventory holding cost for all on-hand inventory used to satisfy demand beyond the last period in the data set.

Figure 8 provides a flowchart depicting the logic of the lot size procedure employed.

Program Validation

Verification of the computer model was obtained through hand calculations and analysis of the results. (Discussed in a separate section.)

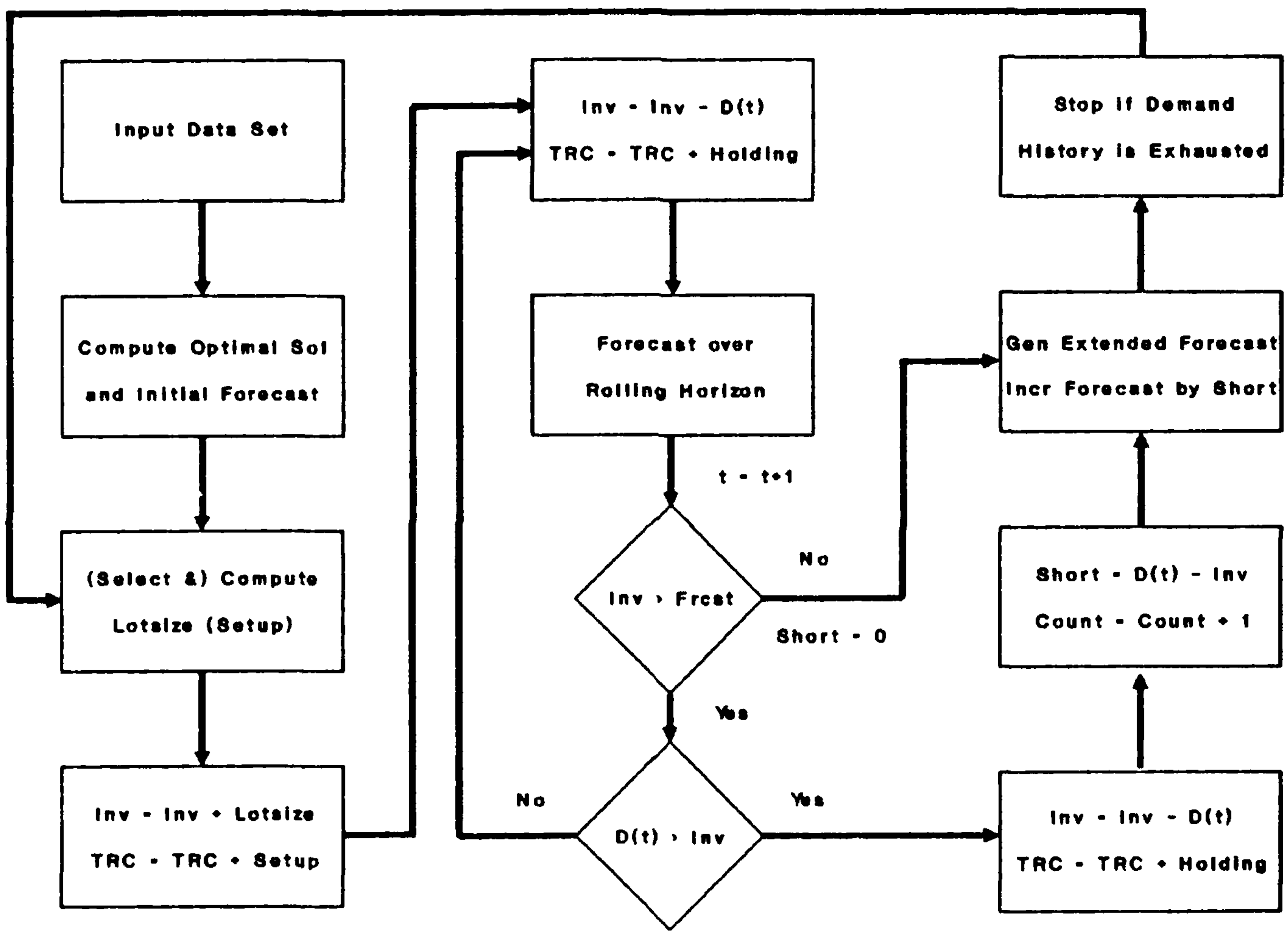


Figure 8 -- Production Procedure (Flow Chart)

The optimal Wagner-Whitten procedure and all lot size heuristics were validated by hand using a data set from the first group. The forecast model used for hand verification of the heuristics was simple exponential smoothing with an alpha parameter of 0.2. The code used for the Wagner-Whitten procedures was an equivalent branch and bound algorithm published by Jacobs and Khumawala (1987). Verification of the code was accomplished by comparing the results with solutions obtained using the Wagner-Whitten algorithm by hand.

The forecast procedure was also validated by hand, however, the overall focus forecasting policy was not. Instead, we validated the model during program development by comparing the focus MAD with each individual MAD for several data sets. The focus forecast compared very favorably, i.e., while not the best, it was significantly better than most.

Verification of the general lot size procedure was also obtained by hand. Specifically, the heuristics were run using the example forecast and the results for each transaction printed out for verification. The policy was then computed by hand and compared with the printout.

EXPERIMENTAL DESIGN

The experimental designs for each group of data was different due to the limited number of data sets available in the second group.

The first group uses an unbalanced 5 factor design with 5 performance criteria (3 of which are the costs outlined previously; the other 2 are measurements involving the mean absolute deviation of the forecast series). The design is unbalanced since 3 of the 5 factors, data set, data type, and degree of variation, are attributes associated with the data set. (By data set, we mean the specific data set of which there are 36. Data type and degree of variation are as defined earlier in our discussion of the sample data and are nested within data set.) The other two factors are, of course, the lot size algorithm and TBO.

The TBO factor was set at 5 levels: 2, 4, 6, 8, and 10. To do this, we set the TBO level a-priori and determined the appropriate A/h ratio based upon the mean or average demand of each data set. Our procedure is therefore similar to the studies performed by Berry (1972), Callarman and Hamrin (1979), Wemmerlöv and Whybark (1984), and others.

All interactions are considered except the 5-way interaction (as it's equivalent to the error term). The second group was handled slightly differently in that only the primary factors, lot size algorithm and TBO, are used in the ANOVA, i.e., we employ a simple 3-factor balanced design with interaction.

RESULTS

The results for both data groups are very similar, however the 3 factor design for the second group wasn't able to discriminate as well as the 5 factor unbalanced design of the first. The ANOVA results are presented in Table 3.

Variable	Significance	
	Group 1	Group 2
Cost	0.001	0.001
Short	0.001	0.001
% Short	0.001	0.006

Table 3. Basic ANOVA

As you can see, both ANOVAs are significant. Tables 4 and 5 provide a "breakdown" of the significance for each factor combination for Groups 1 and 2, respectively. The asterisk denotes significance at the 0.01 level.

The 3- and 4-way interactions are generally significant for cost although not for shortages or amounts short in the Group 1 ANOVA. Results are similar for the 2-way interactions in Group 2. The results for all common factors and their interactions are generally the same for both groups, e.g., the LOT(size) factor is significant whereas the TYPE factor is not. (Note: This is not necessarily true for all dependent variables or "costs".)

Factor	Significance		
	Cost	Short	%Short
LOT	0.0001*	0.0001*	0.0001*
TBO	0.0001*	0.0001*	0.0006*
TYPE	0.9926	0.3008	0.0001*
VAR	0.0001*	0.0001*	0.0001*
SET(VARxTYPE)	0.0001*	0.0001*	0.0001*
LOTxTBO	0.0001*	0.0001*	0.0001*
LOTxTYPE	0.5518	0.4180	0.6018
LOTxVAR	0.0030*	0.0489	0.1056
LOTxSET(VARxTYPE)	0.0001*	0.0001*	0.0009*
TBOxTYPE	0.4834	0.3676	0.3004
TBOxVAR	0.0001*	0.0001*	0.0037*
TBOxSET(VARxTYPE)	0.0001*	0.0036*	0.0001*
VARxTYPE	0.0126	0.0010*	1.0000
LOTxTBOxTYPE	0.0693	0.8679	0.5761
LOTxTBOxVAR	0.0001*	0.2513	0.5739
LOTxTYPExVAR	0.0001*	0.2142	0.7851
TBOxTYPExVAR	0.0001*	0.0734	0.0005*
LOTxTBOxTYPExVAR	0.0001*	0.6336	0.4499

Table 4. Detailed ANOVA (Group 1)

Factor	Significance		
	Cost	Short	%Short
LOT	0.0001*	0.0001*	0.0047*
TBO	0.0001*	0.0001*	0.0180
SET	0.0124	0.3534	0.0023*
LOTxTBO	0.0001*	0.0004*	0.4349
LOTxSET	0.0001*	0.1247	0.0146
TBOxSET	0.0011*	0.2736	0.0067*

Table 5. Detailed ANOVA (Group 2)

Tables 6 and 7 give the results of the Tukey multiple range tests for each single factor of interest.

Means with the same letters are not significantly different and are listed from high to low. Note that the

Factor	Cost	Short	%Short
Lotsize	5 1 3 2 4 A B CCCCC	4 2 3 1 5 AAA C BBB D	4 2 3 1 5 AAA CCC D BBB
TBO	X 8 2 6 4 A BBB CCC	X 8 6 4 2 A BBBBB C	X 4 2 6 8 AAA BBBBBBB
Type	Lin Non AAAAAAA	Lin Non AAAAAAA	Lin Non A B
Var	3 2 1 A B C	3 2 1 A B C	3 2 1 A B C

Table 6. Single Factor Tukey Results (Group 1)

Factor	Cost	Short	%Short
Lotsize	5 1 4 3 2 A BBBBBBB	2 3 4 1 5 AAAAAAA BBB	4 2 3 1 5 AAAAAAAAA
TBO	X 8 2 6 4 A BBBBBBB	X 8 6 4 2 AAAAAAA BBB	X 8 6 2 4 AAAAA CCC BBB

Table 7. Single Factor Tukey Results (Group 2)

lotsize heuristics are classified as before, i.e., 1 = Eisenhut, 2 = EOQ, 3 = Silver-Meal, 4 = Tsado's method, and 5 = Wagner-Whitten (non-optimal). The X denotes a TBO of 10, "Lin" is short for linear, and non-linear is abbreviated as "Non".

There are 8 2-factor interactions of interest which are significant in the Group 1 ANOVA: LOTxTBO and TBOxVAR for cost, number of shortages, and amounts short, LOTxVAR for cost, and VARxTYPE for shortages. Figures 9 through 16 depict these interactions. Figures 17 and 18 provide the results of 2 significant 2-factor interactions, LOTxTBO for both cost and number of shortages from the Group 2 ANOVA.

All interactions involving the (data)SET factor are omitted as differences in cost due to the demand series is expected.

The reader is referred to Appendices D and E for additional information.

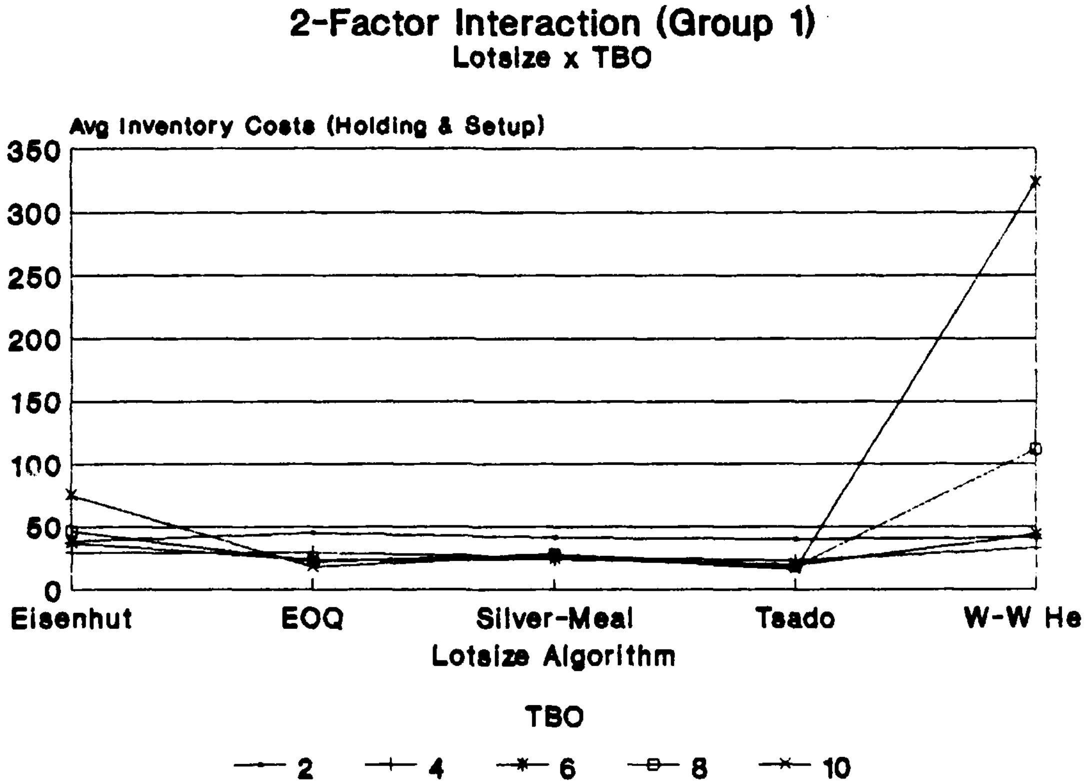

2-Factor Interaction (Group 1)
Lotsize x TBO
Avg Inventory Costs (Holding & Setup)
350
300
250
200
150
100
50
0
Eisenhut
EOQ
Silver-Meal
Tsado
W-W He
Lotsize Algorithm
TBO
2
4
6
8
10

Figure 9

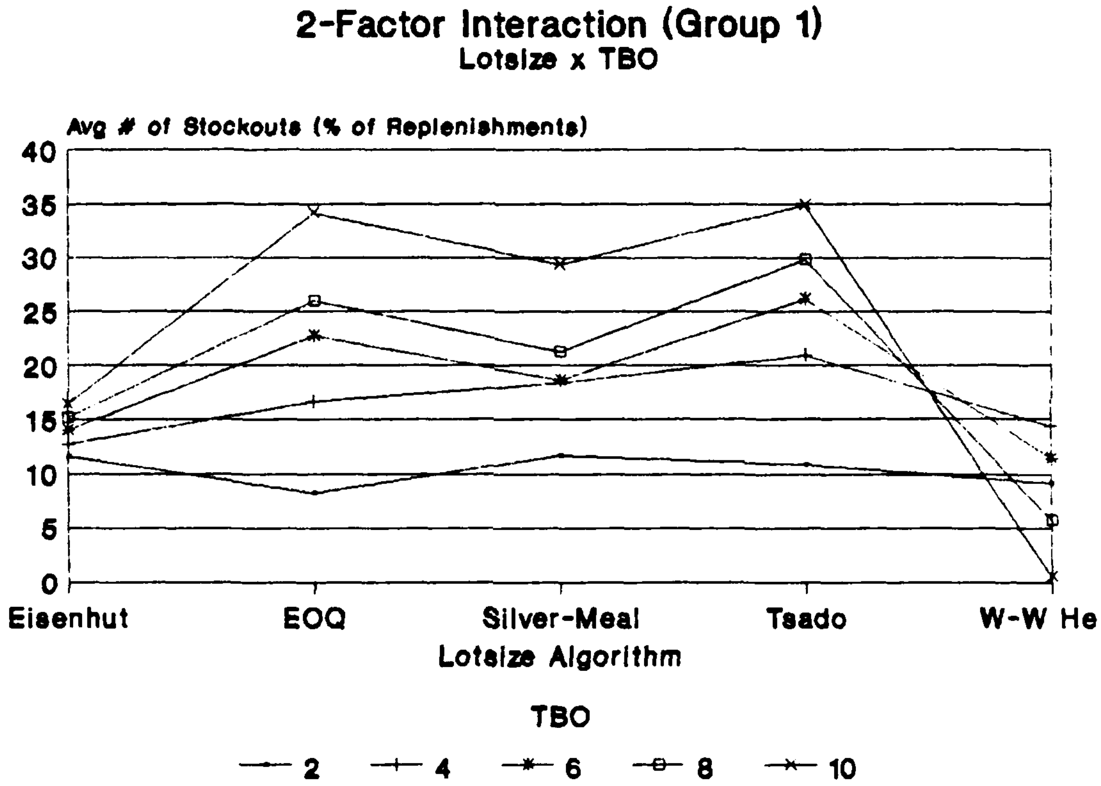

2-Factor Interaction (Group 1)
Lotsize x TBO
Avg # of Stockouts (% of Replenishments)
40
35
30
25
20
15
10
5
0
Eisenhut
EOQ
Silver-Meal
Tsado
W-W He
Lotsize Algorithm
TBO
2
4
6
8
10

Figure 10

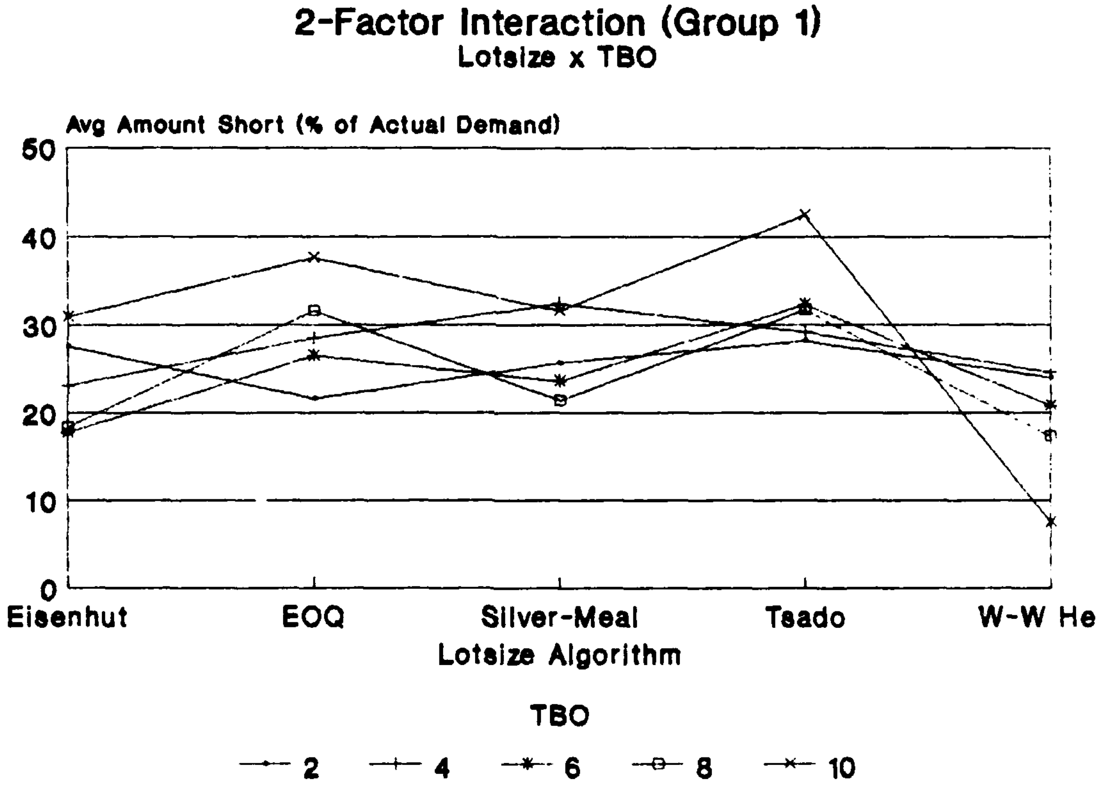

2-Factor Interaction (Group 1)
Lotsize x TBO
Avg Amount Short (% of Actual Demand)
50
40
30
20
10
0
Eisenhut
EOQ
Silver-Meal
Tsado
W-W He
Lotsize Algorithm
TBO
2
4
6
8
10

Figure 11

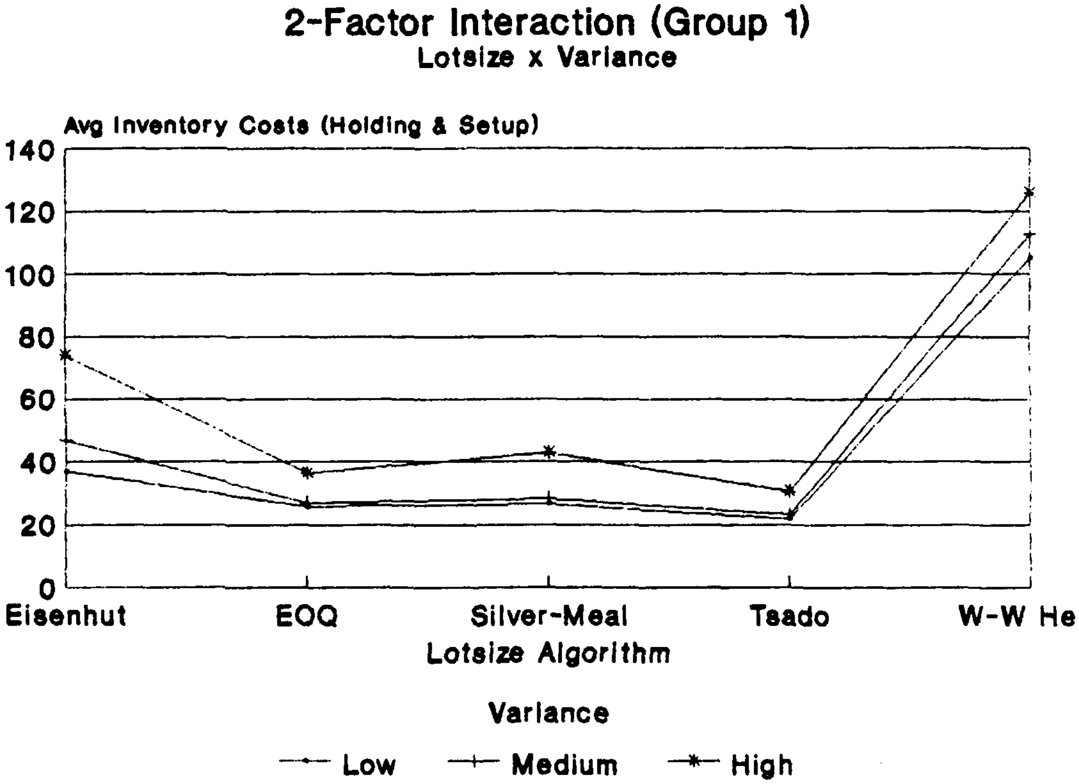

2-Factor Interaction (Group 1)
Lotsize x Variance
Avg Inventory Costs (Holding & Setup)
140
120
100
80
60
40
20
0
Eisenhut
EOQ
Silver-Meal
Tsado
W-W He
Lotsize Algorithm
Variance
Low
Medium
High

Figure 12

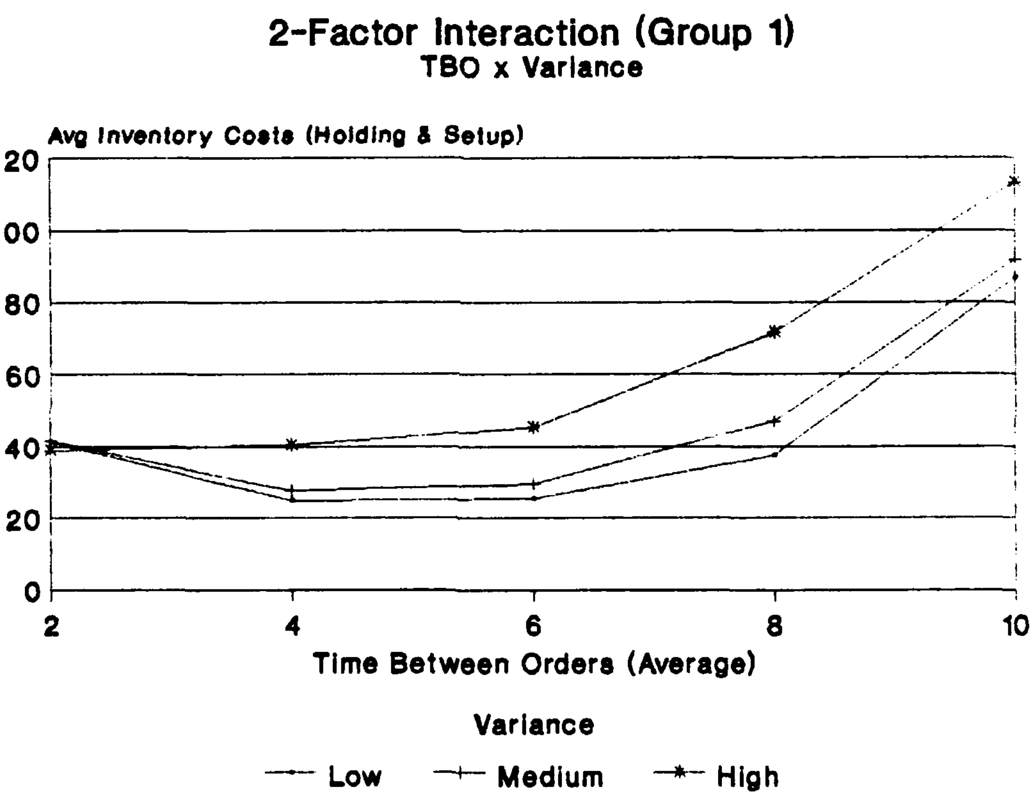
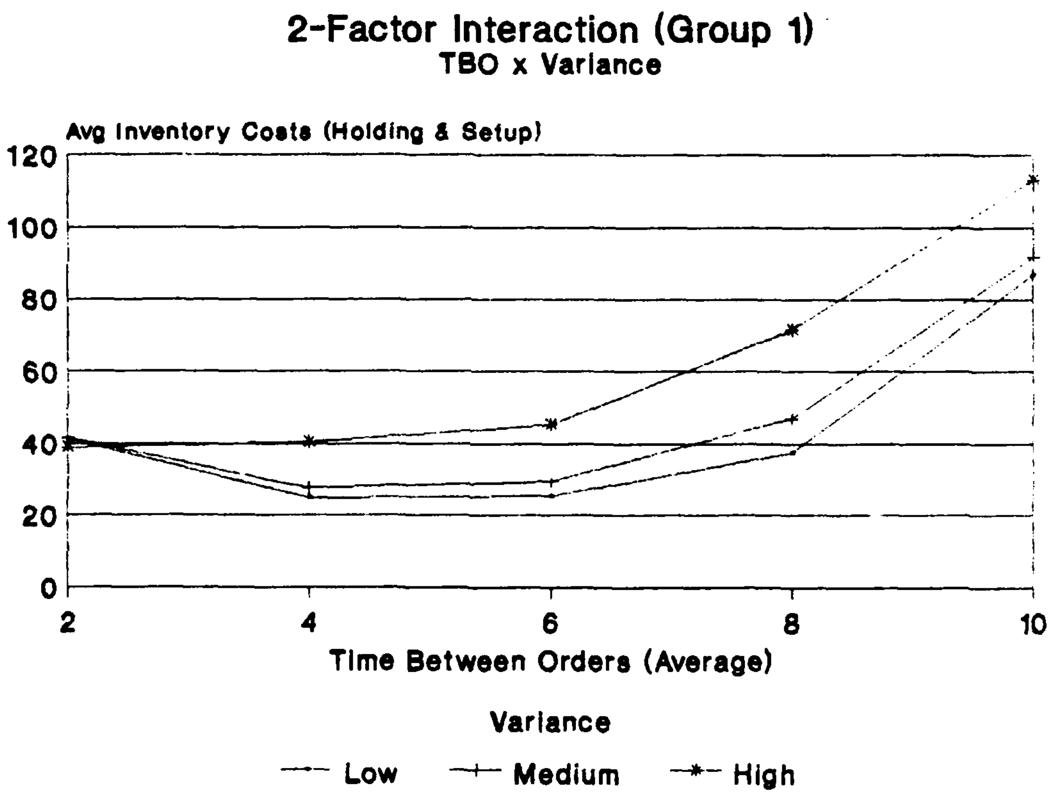

2-Factor Interaction (Group 1)
TBO x Variance
Avg Inventory Costs (Holding & Setup)
120
100
80
60
40
20
0
2
4
6
8
10
Time Between Orders (Average)
Variance
Low
Medium
High

Figure 13



2-Factor Interaction (Group 1)
TBO x Variance
Avg Inventory Costs (Holding & Setup)
120
100
80
60
40
20
0
2
4
6
8
10
Time Between Orders (Average)
Variance
Low
Medium
High

Figure 13

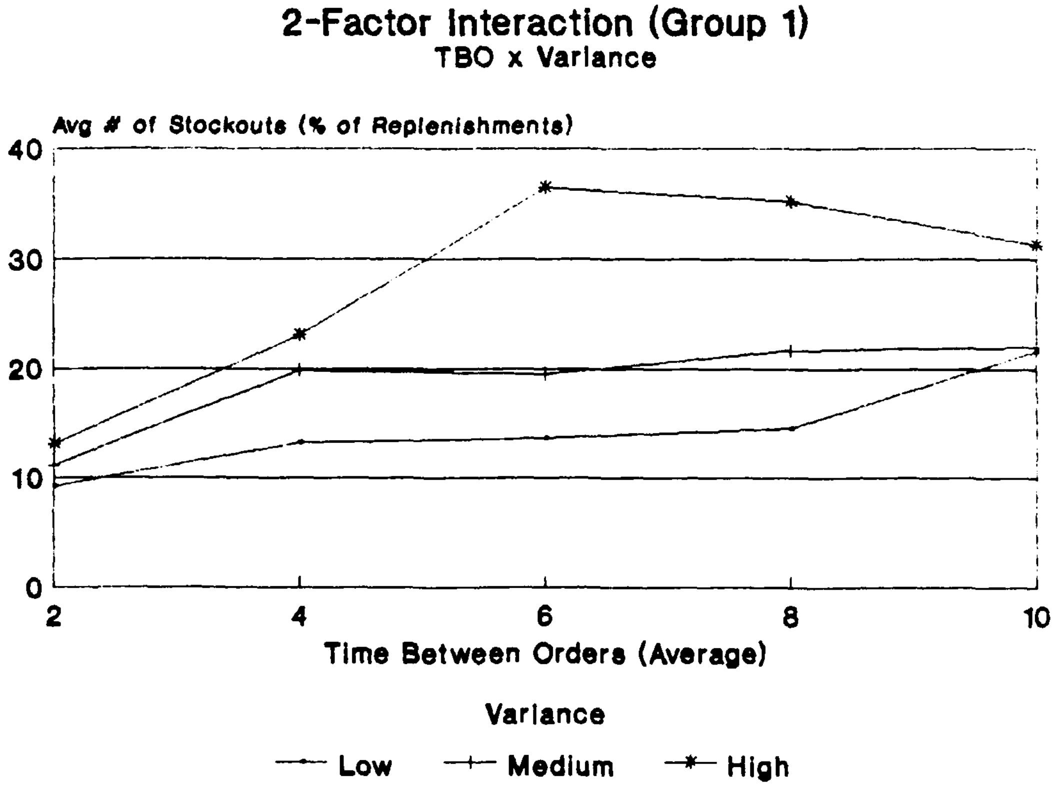

2-Factor Interaction (Group 1)
TBO x Variance
Avg # of Stockouts (% of Replenishments)
40
30
20
10
0
2
4
6
8
10
Time Between Orders (Average)
Variance
Low
Medium
High

Figure 14

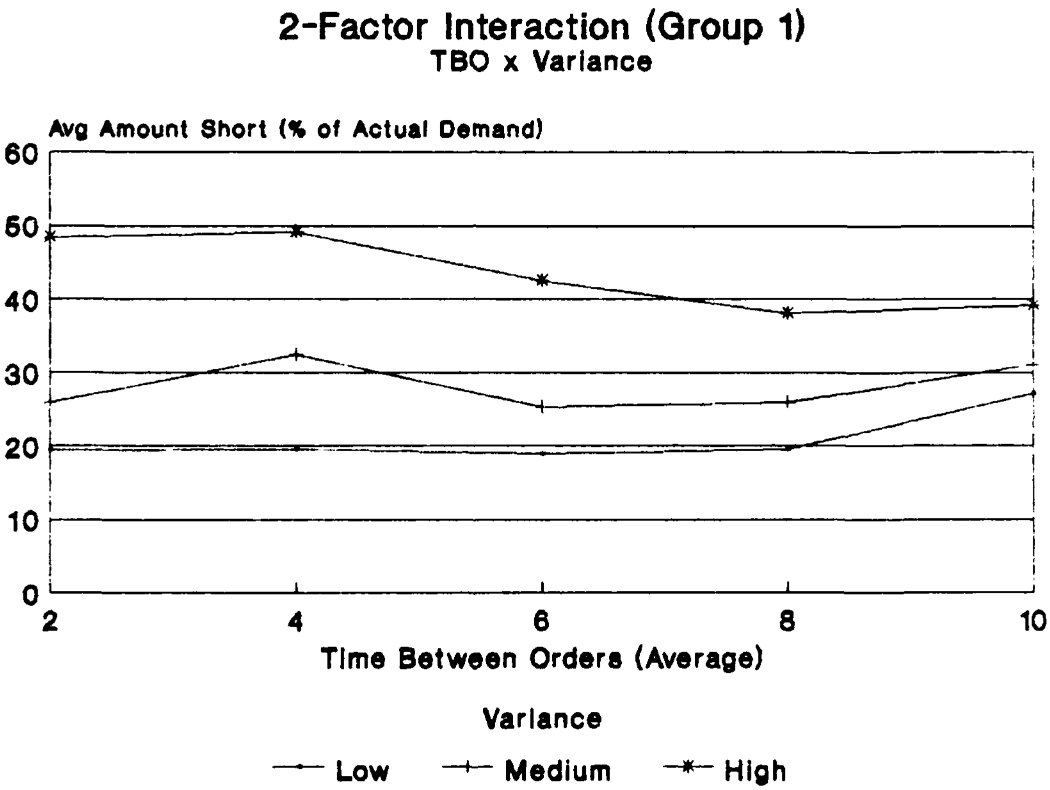

2-Factor Interaction (Group 1)
TBO x Variance
Avg Amount Short (% of Actual Demand)
60
50
40
30
20
10
0
2
4
6
8
10
Time Between Orders (Average)
Variance
Low
Medium
High

Figure 15

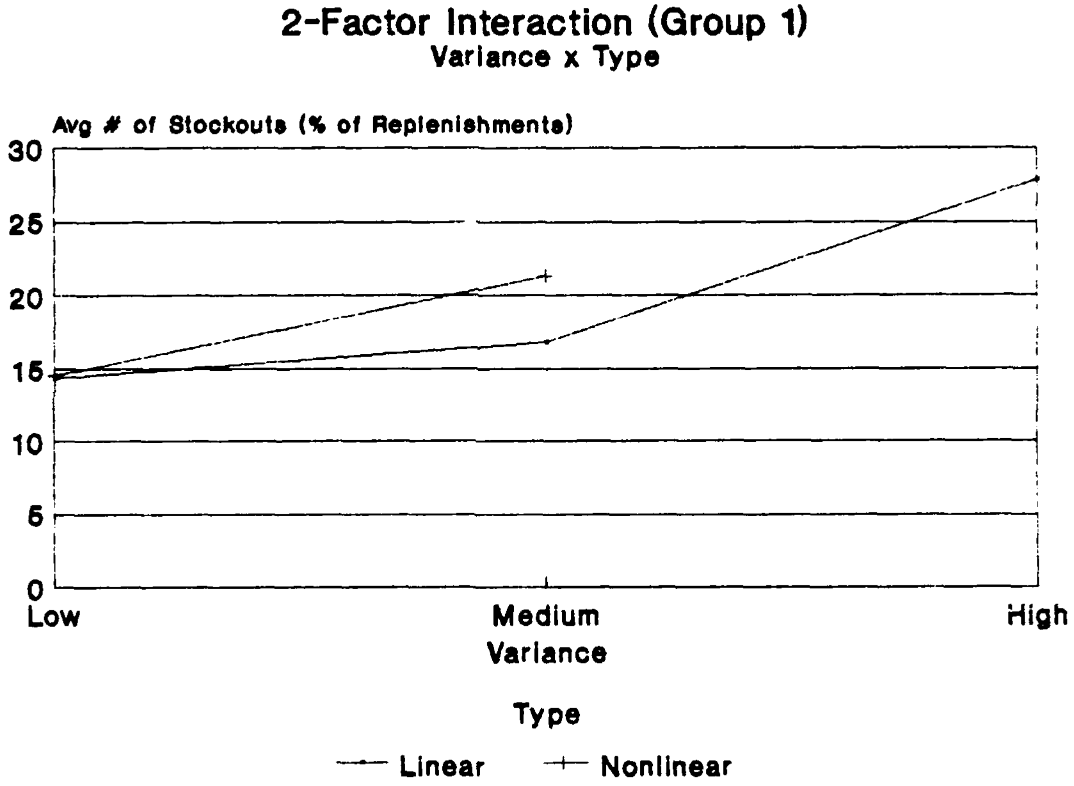

2-Factor Interaction (Group 1)
Variance x Type
Avg # of Stockouts (% of Replenishments)
30
25
20
15
10
5
0
Low
Medium
High
Variance
Type
Linear
Nonlinear

Figure 16

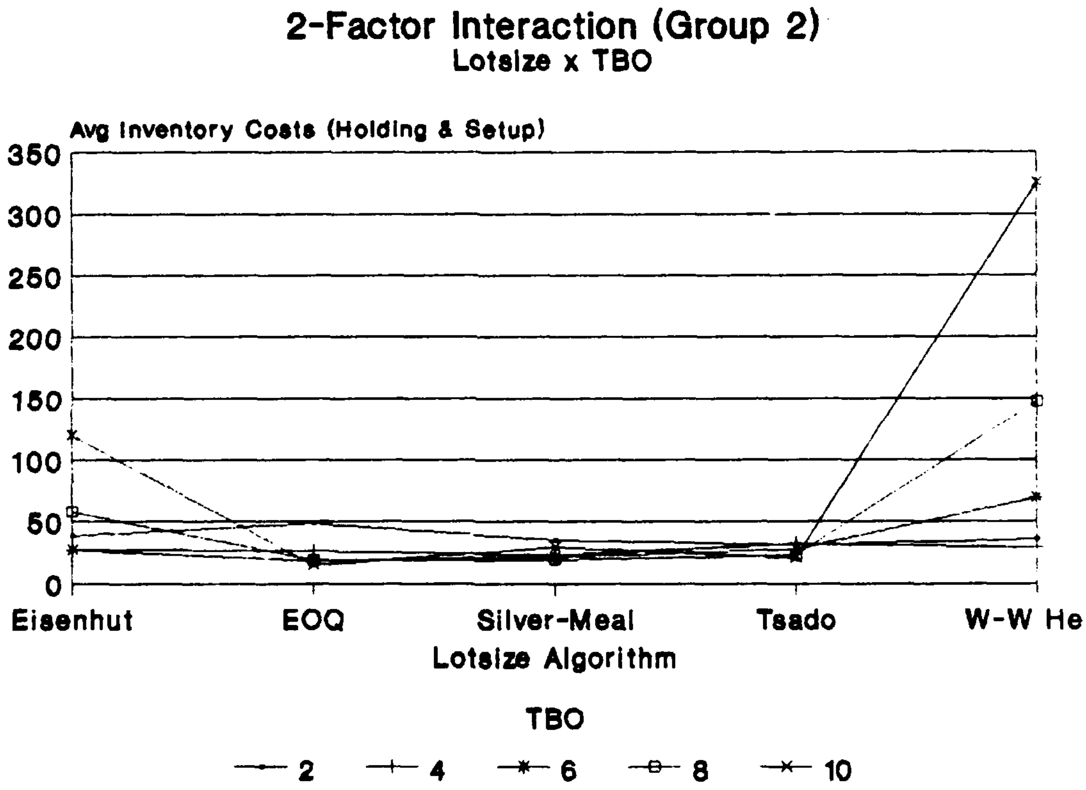

2-Factor Interaction (Group 2)
Lotsize x TBO
Avg Inventory Costs (Holding & Setup)
350
300
250
200
150
100
50
0
Eisenhut
EOQ
Silver-Meal
Tsado
W-W He
Lotsize Algorithm
TBO
2
4
6
8
10

Figure 17

2-Factor Interaction (Group 2)
Lotsize x TBO

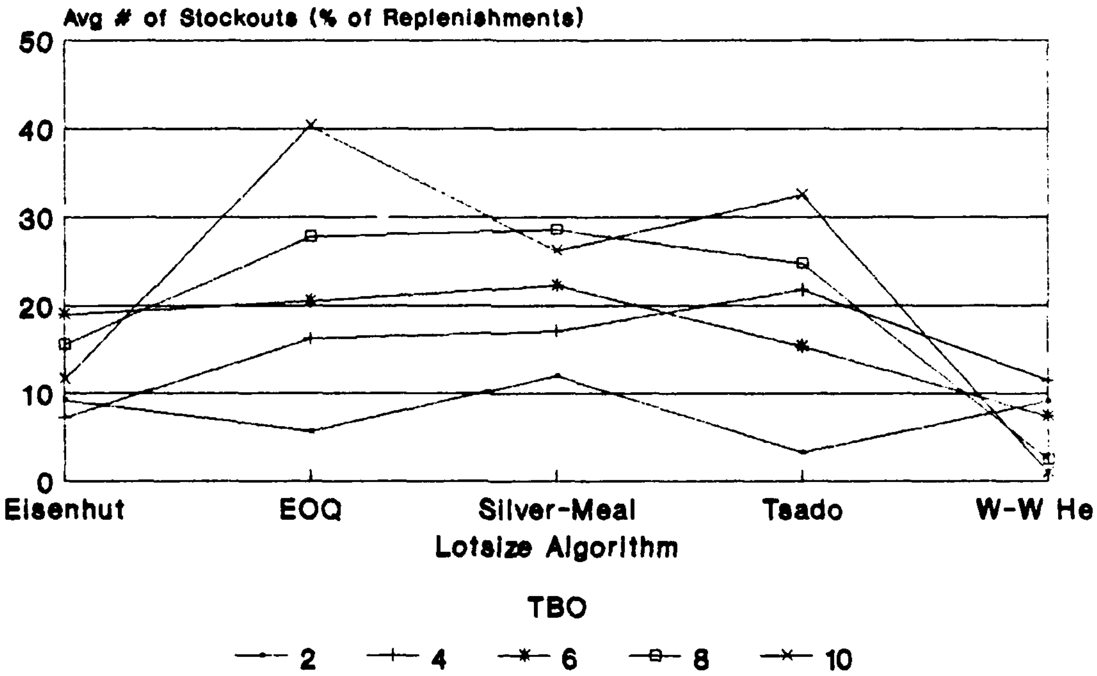


Figure 18

ANALYSIS

It's obvious from Tables 6 and 7 that different lotsize algorithms perform differently for standard inventory (holding and setup) costs than for shortage related "costs".

In this study, we've shown that the EOQ, Silver-Meal, and Tsado algorithms perform significantly better for inventory costs than do the Eisenhut or Wagner-Whitten heuristics. Further, the inventory costs for the LOTxTBO interaction depicted in Figure 9 are relatively stable for these "near-optimal" performers.

Tsado's algorithm performed best for cost (and worse for shortages) in the Group 1 ANOVA, although the differences were not significant between the 3 best. The Group 2 ANOVA placed Tsado's heuristic in third, but again, the differences among the best performers were not significant.

Conversely, the Eisenhut and Wagner-Whitten heuristics perform significantly fewer shortages and less items short per stockout (expressed as a percentage of actual demand for the stockout period). Figures 10 and 11 show the relatively wide range of performance for the various heuristics.

Eisenhut tends to be the most stable for TBO with shortages occurring between 12 and 18 percent of the replenishments made. Wagner-Whitten, while slightly less stable, is the overall best performer. It's interesting to note that performance of the W-W heuristic as a "function of" TBO is essentially inverted. Figure 11 shows a much greater degree of interaction between all five heuristics for amounts short.

Note that a TBO of 10 provides the W-W solution with virtually no stockouts and less than 10 percent of actual demand short when a stockout does occur. The price, however, is an average cost over 3 times as great as the true optimal solution. In all cases, the Wagner-Whitten algoritnm performed worse for cost and best for shortages, although significance was not shown for amounts short in the Group 2 ANOVA (see Table 7).

It therefore appears the Wagner-Whitten and Eisenhut algorithms maintain a significant amount of inherent safety stock whereas the others tend to "run lean". Additional inventory would drive up the inventory holding costs while reducing the number of stockouts due to being a few items short.

Table 6 shows the type of data set, i.e., whether it's linear or non-linear, does not affect either cost or the number of shortages significantly. Non-linearity does seem to affect the amount short per stockout. It appears that non-linear demand has a smaller percentage short per stockout due to "over-forecasting" by our linear forecast model. The degree of variance, however, is significant for all dependent variables with lower overall costs associated with lower variability (as would be expected).

Although the significance level was set at 0.01, Figure 13 (TBOxVAR - Cost) shows interaction between TBO levels of 2 and 4. Although lower variance generally implies lower overall costs (i.e., both inventory and shortage related), the reverse is true for the TBO factor at a level of 2. We would like to point out that actual cost performance at this level may not be that "significant" (41.3, 41.7, and 39.0 for low, medium, and high variances, respectively).

Cost performance as a function of TBO tends to validate the "rule of thumb" advocated by Wemmerlöv and Whybark (1984) which states the length of the rolling horizon should be approximately 3 times the average time between orders. A TBO of 4 was best using our rolling horizon of 12 periods. Performance for number of stockouts and amounts short per stockout, however, do not support this assertion.

We should note at this point that Wemmerlöv and Whybark (1984) also advocate a rolling horizon of at least 5 times the average time between orders for the Wagner-Whitten algorithm when used as a heuristic. The argument in this case was the fact the W-W heuristic utilized the entire length of the rolling horizon in order to make its initial production decision. From Appendix D, we see that the mean cost performance for the W-W heuristic for a TBO of 2 is 41.015926 and for a TBO of 4 is 32.546886. This tends to discredit their assertion.

There may be 2 reasons for this. First, previous cost criteria "consisted" of standard inventory costs and an "artificial" service level. The mean "cost" performance for stockouts is better for the Wagner-Whitten heuristic with a TBO of 2 than a TBO of 4 (9.1463710 and 14.3588956, respectively), therefore the "total costs" due to inventory and stockouts may "average" out. (Note there was no real difference in the amounts short for either case.) Second, forecasts generally tend to "worsen" as they extend further into the future. This would tend to imply that using increasingly "bad" data in order to make the initial production decision results in a "worse" decision.

The cost results for the TBO factor (where a TBO which is one-third of our rolling horizon is "optimal") tend to validate the production procedure and the computer code in general.

Other results which tend to validate this research are as follows:

1. The difference between all heuristic costs and the optimal cost are strictly positive.

2. The average difference between the mean absolute

deviation of the lotsize forecasts and the focused forecast for each data set is strictly positive.

3. The amount of lotsize forecast error decreases with TBO.

4. Lotsize forecast error is greater for non-linear than for linear data sets.

5. Lotsize forecast error is generally greater for data sets with a higher degree of variance.

And finally, we would like to note that the Group 2 design did not discriminate as well as the Group 1 design. This is probably due to 2 factors. First, the number of datasets, and therefore observations, is smaller in Group 2 than Group 1. Second, the design for Group 1 is more "complex", i.e., it accounts for more error than the simpler Group 2 model. It's interesting to note, however, that Figures 17 and 18 show essentially the same thing as Figures 9 and 10, i.e., both data groups (Groups I and II) show approximately the same average performance, both absolute (numerically) and relative (to each other), for all lotsize algorithms at all factor levels.

CHAPTER VI

CONCLUDING REMARKS

The purpose of this research was three-fold. First, there existed a need to perform a study of lotsize heuristic performance which forecasts empirical demand data in the same manner in which the lotsize heuristics are implemented, i.e., over a rolling horizon. Second, we wished to analyze shortage costs separately from traditional inventory costs. And finally, we wished to validate the heuristic presented by Tsado (1985).

The lack of significance for the LOTxVAR interaction validates the assertion of previous studies that, although higher variance increases costs, it doesn't alter the relative performance of the lot size heuristics.

We have shown, however, that results from previous studies were confounded due to the way shortage costs were handled, i.e., by setting an arbitrary service level. Whereas previous studies showed no significant difference in lot size heuristic performance, we have shown that some lot size heuristics perform better for traditional inventory costs and others perform better with regard to the average number of stockouts expressed as a percentage of the total number of replenishments made and average amounts short as a percentage of actual demand for the stockout period.

Whether this result has any application to the way lotsize heuristics are chosen and implemented or not is for industry to decide. (Specifically, a company will probably set a service level based upon its own perception of the "cost" associated with a shortage.) However, we believe this result is important in that it shows that researchers should carefully choose their basic assumptions. In this case, previous researchers would have obtained results similar to this research if they had set service level as a factor in their experimental designs. But by setting a single service level, they "confounded" the relative performance of the various lot size heuristics examined.

And finally, we've shown that Tsado's algorithm performed very well for traditional inventory holding and setup costs and have therefore validated his 1985 study.

This study was by no means all-encompassing. The following are suggestions for further research:

1. A similar study is required using a balanced experimental design similar to that used by Group 1 and using a more complete array of lotsize techniques.

2. Separate research regarding the relative merit of focus or "adaptive" and averaged exponential smoothing techniques (as used in automatic forecasting over a rolling horizon) is warranted.

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APPENDIX A

GROUP 1 DATA

PERIOD/SET	1	2	3	4	5
1	48	17	39	26	26
2	38	8	137	22	27
3	59	20	54	33	47
4	50	22	11	27	52
5	50	5	23	28	37
6	72	16	20	32	33
7	72	17	9	24	33
8	90	2	2	3	6
9	60	15	7	44	31
10	69	24	7	41	38
11	73	25	8	26	37
12	90	22	9	28	34
13	71	7	13	91	27
14	913	172	12	35	29
15	86	35	15	38	34
16	402	34	153	30	27
17	73	25	21	27	29
18	92	22	4	32	28
19	81	20	4	33	31
20	86	12	13	39	26
21	89	12	16	46	26
22	112	11	18	55	32
23	54	6	16	55	26
24	54	6	15	55	34
25	69	10	20	39	27
26	52	13	13	29	34

PERIOD/SET	1	2	3	4	5
27	54	17	22	35	20
28	54	13	23	36	39
29	39	2	13	28	34
30	48	10	18	35	27
31	27	8	16	25	24
32	58	14	195	36	31
33	32	8	335	27	29
34	47	10	37	27	16
35	48	14	15	27	26
36	56	25	5	28	19
37	67	18	18	25	49
38	87	21	13	38	36
39	58	21	23	31	32
40	58	21	21	18	22
41	66	20	17	90	28
42	61	33	20	84	13
43	73	18	15	24	19
44	80	12	17	41	15
45	62	10	30	23	22
46	48	10	144	20	26
47	68	11	14	22	25
48	51	12	12	16	19
49	47	14	7	17	20
50	53	10	14	23	31
51	49	10	29	23	21
52	51	9	61	40	42

PERIOD/SET	6	7	8	9	10
1	22	26	103	35	64
2	16	26	77	37	52
3	21	44	81	35	64
4	14	43	67	48	80
5	23	47	96	54	69
6	22	33	83	43	55
7	12	39	86	57	56
8	3	9	12	2	15
9	31	19	189	154	80
10	23	31	107	60	70
11	23	15	86	49	70
12	31	30	100	37	64
13	27	20	165	118	66
14	34	25	157	48	66
15	23	30	130	88	92
16	21	22	238	187	84
17	21	33	126	75	63
18	23	36	81	42	82
19	38	33	104	59	83
20	21	27	94	52	85
21	24	27	129	53	89
22	20	23	103	39	67
23	31	18	101	45	73
24	28	17	133	76	89
25	25	11	219	140	85
26	24	14	135	64	65

PERIOD/SET	6	7	8	9	10
27	18	10	130	80	81
28	25	29	239	112	77
29	18	21	122	100	71
30	9	16	105	54	66
31	13	15	87	32	66
32	22	19	80	67	76
33	15	11	70	74	66
34	20	11	88	45	73
35	32	23	96	50	74
36	29	30	180	116	63
37	26	24	139	100	73
38	26	29	126	78	68
39	21	28	89	10	73
40	17	17	93	52	60
41	19	28	231	141	49
42	15	40	123	73	49
43	17	23	128	36	50
44	12	33	60	41	48
45	21	31	85	57	54
46	15	31	73	36	52
47	11	23	61	42	56
48	14	23	71	36	41
49	15	26	58	20	36
50	17	26	81	66	48
51	20	22	67	39	39
52	13	26	113	58	67

PERIOD/SET	6	7	8	9	10
27	18	10	130	80	81
28	25	29	239	112	77
29	18	21	122	100	71
30	9	16	105	54	66
31	13	15	87	32	66
32	22	19	80	67	76
33	15	11	70	74	66
34	20	11	88	45	73
35	32	23	96	50	74
36	29	30	180	116	63
37	26	24	139	100	73
38	26	29	126	78	68
39	21	28	89	10	73
40	17	17	93	52	60
41	19	28	231	141	49
42	15	40	123	73	49
43	17	23	128	36	50
44	12	33	60	41	48
45	21	31	85	57	54
46	15	31	73	36	52
47	11	23	61	42	56
48	14	23	71	36	41
49	15	26	58	20	36
50	17	26	81	66	48
51	20	22	67	39	39
52	13	26	113	58	67

PERIOD/SET	11	12	13	14	15
1	40	24	48	13	6
2	43	29	45	21	9
3	42	34	55	29	11
4	51	29	51	26	12
5	46	23	59	20	11
6	59	18	41	36	17
7	49	27	59	16	8
8	10	5	11	12	7
9	63	32	59	12	33
10	61	32	61	16	28
11	54	31	66	9	35
12	57	31	74	7	32
13	85	27	74	12	35
14	48	30	210	12	40
15	76	30	109	11	43
16	72	27	202	12	41
17	48	39	35	8	37
18	59	24	53	10	35
19	62	35	52	9	40
20	50	30	41	8	38
21	54	37	39	12	42
22	69	26	49	7	45
23	51	28	49	5	35
24	66	31	46	15	46
25	52	25	48	9	40
26	57	38	50	9	27

PERIOD/SET	11	12	13	14	15
27	59	2	58	7	36
28	73	60	65	12	34
29	46	41	62	9	29
30	68	35	82	11	46
31	48	35	139	13	30
32	52	39	162	10	42
33	51	35	84	11	25
34	58	31	58	9	35
35	49	39	63	6	37
36	47	42	36	6	24
37	52	35	75	20	50
38	62	42	97	15	43
39	66	38	62	10	40
40	35	42	102	10	25
41	45	30	41	15	22
42	49	37	56	14	14
43	35	30	46	15	14
44	40	29	50	9	10
45	34	63	62	11	10
46	56	79	51	15	13
47	36	21	47	14	14
48	29	28	57	12	14
49	32	28	56	13	7
50	32	39	69	9	17
51	36	32	69	14	12
52	65	54	135	21	19

PERIOD/SET	16	17	18	19	20
1	51	22	10	38	3
2	47	6	12	21	16
3	41	19	23	88	18
4	45	50	6	57	13
5	29	29	54	82	22
6	56	32	7	52	8
7	55	40	33	60	22
8	8	3	3	9	4
9	32	29	12	68	15
10	42	33	9	67	25
11	40	33	10	65	48
12	48	36	12	61	38
13	39	34	14	44	228
14	56	38	10	74	65
15	38	154	12	59	93
16	15	49	9	43	68
17	39	56	17	48	73
18	42	42	28	41	80
19	38	51	26	49	48
20	53	22	19	64	66
21	36	30	11	60	51
22	46	32	27	51	113
23	61	27	24	32	86
24	45	23	26	38	66
25	38	63	5	38	76
26	35	27	13	34	59

PERIOD/SET	16	17	18	19	20
27	26	22	9	36	217
28	50	21	26	44	74
29	47	17	18	36	118
30	49	28	10	45	113
31	13	22	9	60	55
32	184	384	22	38	107
33	61	23	6	38	90
34	56	12	20	32	96
35	43	13	9	18	90
36	50	11	19	53	104
37	29	14	10	56	57
38	69	29	7	61	107
39	32	23	11	52	35
40	35	15	42	36	26
41	44	10	21	38	28
42	60	47	17	42	20
43	41	11	4	41	22
44	54	11	16	56	15
45	63	26	7	33	30
46	56	5	13	48	27
47	45	28	8	41	10
48	41	17	15	27	26
49	50	12	12	36	10
50	45	22	9	40	12
51	49	10	10	47	409
52	100	31	9	38	21

PERIOD/SET	21	22	23	24	25
1	15	11	12	132	26
2	24	24	11	50	34
3	30	26	13	145	34
4	29	13	22	59	46
5	28	18	20	50	44
6	22	8	14	43	37
7	30	22	14	104	41
8	3	7	3	3	3
9	27	17	25	376	76
10	38	12	59	121	35
11	38	18	43	68	61
12	22	24	42	55	33
13	51	17	23	36	69
14	45	19	33	43	43
15	28	17	24	17	18
16	42	25	17	67	42
17	30	10	18	100	43
18	31	38	36	60	35
19	33	21	20	79	29
20	47	27	30	52	27
21	20	32	32	101	30
22	44	57	28	56	40
23	13	28	38	63	42
24	48	27	20	86	29
25	65	58	32	55	24
26	45	34	30	59	32

PERIOD/SET	21	22	23	24	25
27	62	42	31	65	23
28	62	33	21	29	34
29	78	29	33	129	39
30	58	113	29	47	32
31	76	39	33	47	31
32	62	41	32	57	38
33	66	46	38	72	27
34	84	52	48	52	43
35	77	37	27	99	27
36	72	87	42	84	41
37	43	44	19	51	39
38	50	45	39	74	30
39	39	35	37	49	39
40	46	28	22	44	32
41	42	35	14	35	24
42	44	32	14	60	39
43	32	21	12	31	27
44	50	18	12	66	31
45	22	30	15	73	77
46	39	25	6	56	38
47	42	31	15	61	52
48	28	35	6	53	23
49	21	12	9	43	33
50	28	16	15	46	31
51	16	9	8	57	16
52	24	20	18	82	51

PERIOD/SET	26	27	28	29	30
1	155	14	12	13	13
2	102	14	3	14	17
3	83	17	5	32	22
4	112	19	9	25	14
5	84	18	5	28	20
6	99	18	5	33	13
7	117	16	4	32	11
8	9	1	1	6	7
9	212	9	6	9	14
10	88	15	7	7	14
11	130	10	3	12	17
12	148	17	9	10	12
13	209	13	4	8	15
14	150	12	5	14	15
15	236	16	6	11	14
16	112	16	5	5	19
17	147	6	5	10	21
18	94	20	4	4	8
19	132	17	6	9	14
20	97	17	9	7	11
21	113	23	7	14	9
22	200	16	5	9	11
23	117	22	8	6	9
24	124	17	12	10	12
25	120	19	5	10	11
26	56	16	8	8	11

PERIOD/SET	26	27	28	29	30
27	105	28	5	11	10
28	99	22	3	15	2
29	149	10	6	8	12
30	88	23	5	10	9
31	78	19	5	9	11
32	96	19	3	3	12
33	103	28	6	15	12
34	102	23	8	12	12
35	103	19	6	9	15
36	102	30	7	11	13
37	82	16	3	10	13
38	165	15	4	15	10
39	76	13	5	11	15
40	79	14	4	11	15
41	59	11	6	13	12
42	108	10	5	13	12
43	88	13	8	11	22
44	85	9	8	12	9
45	155	11	5	10	8
46	126	11	9	14	16
47	128	18	8	11	11
48	82	17	9	13	7
49	144	9	9	16	8
50	97	15	9	7	9
51	61	9	8	16	23
52	186	26	21	21	22

PERIOD/SET	31	32	33	34	35
1	23	3	23	22	9
2	29	5	20	17	11
3	18	13	60	37	13
4	19	10	29	10	11
5	41	11	62	29	10
6	11	8	37	28	14
7	19	13	23	16	11
8	1	4	4	1	3
9	5	5	48	25	19
10	23	5	60	31	14
11	35	8	59	33	15
12	41	7	114	29	17
13	40	8	56	23	7
14	14	6	37	21	14
15	83	2	54	30	10
16	32	5	42	39	6
17	16	8	32	17	16
18	47	5	20	25	13
19	22	4	48	22	12
20	23	8	26	40	11
21	93	6	22	16	14
22	25	7	31	28	11
23	22	5	15	17	9
24	21	5	43	17	11
25	33	5	19	13	12
26	23	4	46	20	17

PERIOD/SET	31	32	33	34	35
27	69	5	17	12	18
28	82	5	20	29	12
29	14	1	20	12	14
30	14	8	24	15	15
31	29	5	22	12	14
32	23	6	48	8	7
33	26	8	31	12	9
34	18	3	24	24	10
35	8	2	29	15	11
36	24	1	37	22	8
37	28	6	25	27	10
38	45	9	34	25	5
39	18	10	39	29	11
40	39	2	57	24	4
41	27	4	36	14	4
42	20	6	42	28	7
43	25	7	15	14	10
44	17	4	32	15	9
45	35	6	36	11	7
46	22	5	38	11	5
47	34	5	109	36	8
48	23	4	51	18	4
49	20	8	43	23	11
50	27	3	37	19	6
51	36	3	18	13	7
52	39	9	37	36	14

PERIOD/SET	36
1	31
2	18
3	38
4	16
5	26
6	32
7	21
8	6
9	10
10	19
11	31
12	26
13	29
14	36
15	29
16	55
17	18
18	24
19	48
20	38
21	15
22	49
23	13
24	68
25	14
26	12

PERIOD/SET	36
27	17
28	41
29	13
30	16
31	11
32	28
33	31
34	18
35	1
36	24
37	31
38	21
39	24
40	37
41	13
42	49
43	17
44	31
45	36
46	40
47	90
48	124
49	66
50	64
51	54
52	74

APPENDIX B

GROUP 2 DATA

PERIOD/SET	1	2	3	4	5
1	1053	441	548	783	176
2	1254	558	795	511	92
3	1566	402	993	2116	44
4	1659	234	1103	2998	84
5	1143	363	927	954	124
6	1374	306	831	1299	254
7	1353	189	845	1245	63
8	1296	114	665	1274	141
9	1920	387	888	1151	147
10	1248	444	539	1316	86
11	1104	327	363	804	175
12	909	318	370	488	34
13	945	239	425	832	131
14	870	376	375	2076	47
15	1247	399	451	835	154
16	990	398	348	1124	68
17	1422	281	461	1436	68
18	1359	282	459	1267	137
19	1113	227	437	2020	150
20	1479	340	465	832	73
21	1455	380	401	909	113
22	1029	671	426	718	65
23	998	562	102	646	60
24	966	522	0	656	61
25	627	277	1136	633	24
26	723	341	821	744	64

PERIOD/SET	1	2	3	4	5
27	885	512	848	632	36
28	1323	431	1231	676	27
29	1137	361	928	685	106
30	1389	386	867	819	79
31	1455	3880	656	402	72
32	1110	555	1084	519	38
33	1470	1583	1302	694	61
34	867	2667	1263	531	46
35	1095	2626	997	486	68
36	861	2584	1208	517	26
37	465	1907	1353	247	20
38	771	1540	1038	404	86
39	756	1163	1207	330	29
40	1038	908	1223	245	22
41	1356	863	1002	213	43
42	1521	751	1173	209	34
43	1194	683	802	103	90
44	1158	2231	1548	190	15
45	1569	2578	2309	309	33
46	957	922	882	133	28
47	798	1085	1094	99	15
48	686	1059	1305	168	15
49	633	1162	1918	266	214
50	639	973	1216	180	120
51	894	749	2409	274	108
52	837	971	1907	331	106

PERIOD/SET	1	2	3	4	5
53	918	903	1370	174	136
54	987	974	1136	120	96
55	1035	979	936	78	31
56	840	858	1284	98	72
57	1107	1105	2340	96	156
58	801	1419	1444	121	106
59	714	1119	1530	146	102
60	696	963	1376	171	148
61	570	919	1319	109	96
62	357	937	1480	125	100
63	525	1588	1291	201	108
64	696	876	1407	127	120
65	870	656	1108	110	113
66	570	508	978	139	139
67	657	581	1149	55	151
68	750	867	776	132	92
69	669	1198	1566	84	96
70	474	1368	1216	180	102
71	402	1104	1389	231	148
72	414	1190	1719	135	194
73	315	894	882	127	145
74	402	883	1266	177	153
75	504	887	1499	116	147
76	429	906	1141	175	144
77	372	833	1153	113	157
78	315	697	996	158	197

APPENDIX C

PROGRAM LISTING

```
DECLARE SUB eoq ()
DECLARE SUB tsado ()
DECLARE SUB wwheuristic ()
DECLARE SUB eoqtimesupply ()
DECLARE SUB eisenhut ()
DECLARE SUB silvermeal ()
DECLARE SUB wagnerwhitten ()
DECLARE SUB forecaster ()
COMMON SHARED /Adata/ cost, count, datatype, holding,
                      horizon, inventory, k9
COMMON SHARED /Bdata/ lastn, mad, n, production, setup,
                      sigma, xbar
DEFSNG A-Z
x = 10 'Dummy variable to allow dynamic dimensioning of
        demand(n) and forecast(n)
DIM SHARED D(x), demand(x), forecast(x, x), lotdata(x)
DIM SHARED R(x), a(x, x), O(x)
'Iterate through all 'DATA sets
FOR dataset = 1 TO 5
READ xbar, sigma, datatype, n
horizon = 12   '12 weeks (3 months) for weekly DATA or 12
                months for yearly data
ERASE demand, forecast, D, lotdata
REDIM SHARED D(horizon), demand(n), forecast(n + 1, 2),
             lotdata(n + horizon)
FOR i = 1 TO n: READ demand(i): NEXT i
IF n = 52 THEN lastn = 6 ELSE lastn = 12
'Compute variation as Low (1), Medium (2), or High (3)
IF sigma / xbar <= .5 THEN
    variation = 1
ELSE
    IF sigma / xbar > 1! THEN
        variation = 3
    ELSE
        variation = 2
```

```
    END IF
END IF
'Generate optimal forecast
CALL forecaster
'Begin iterations through all values of TBO
FOR TBO = 2 TO 10 STEP 2
setup = INT(.5 + .5 * xbar * TBO ^ 2): holding = 1
IF n = 52 THEN lastn = 6 ELSE lastn = 12
start = lastn
'Get optimal solution
CALL wagnerwhitten
'Begin iterations through all lotsize algorithms
FOR lotsize = 1 TO 5
IF n = 52 THEN lastn = 6 ELSE lastn = 12
'Start basic algorithm
lastn = lastn + 1: short = 0: count = 0
58 IF lastn > n THEN 2101
FOR i = 1 TO horizon
D(i) = forecast(lastn, 1) + (i - 1) * forecast(lastn, 2)
IF D(i) < 0 THEN D(i) = 0
lotdata(lastn + i - 1) = D(i)
NEXT i
D(1) = D(1) + short
'Select appropriate lotsize technique
ON lotsize GOTO 665, 666, 667, 668, 669
665 CALL eisenhut
GOTO 701
666 CALL eoq
GOTO 701
667 CALL silvermeal
GOTO 701
668 CALL tsado
GOTO 701
669 CALL wwheuristic
'Compute inventory level and cost after production
701 inventory = inventory + production
cost = cost + setup: count = count + 1
'Compute inventory and holding costs after demand for
'current period is satisfied
61 IF lastn > n GOTO 2101
inventory = inventory - demand(lastn) - short
cost = cost + inventory * holding
IF lastn >= n GOTO 2101
lastn = lastn + 1
'Determine if forecast demand exceeds inventory
IF inventory > lotdata(lastn) THEN   'Inventory exceeds
forecast
    IF demand(lastn) > inventory THEN   'Demand too large
                                         -- shortage
        short = demand(lastn) - inventory
        inventory = 0
        percentshort = percentshort + short / demand(lastn)
```

```
        shortcounter = shortcounter + 1
        lastn = lastn + 1
        GOTO 58    'Setup a new production run
    ELSE   'Demand was less than our inventory -- deliver
            current demand
        short = 0
        GOTO 61    'Deliver next period's demand
    END IF
ELSE    'Next period's forecast for demand exceeds current
inventory
    short = 0
    GOTO 58    'Setup a new production run
END IF
'Calculate the true mean absolute deviation for all periods
'included in the lotsize problem
2101 FOR l = start + 1 TO n
lotsizeforecasterror = lotsizeforecasterror +
ABS(lotdata(l) - demand(l))
lotsizetrackingsignal = lotsizetrackingsignal + demand(l) -
lotdata(l)
NEXT l
lotsizeforecasterror = lotsizeforecasterror / (n - start)
lotsizetrackingsignal = lotsizetrackingsignal /
                         (lotsizeforecasterror * (n - start))
'Subtract holding costs for periods beyond N from the total
'cost -- this will reduce the variability between TBOs
'(treatments).
cost = cost - inventory * holding
'Compute PERCENTSHORT if SHORTCOUNTER is nonzero (to
'prevent division by 0).
IF shortcounter > 0 THEN percentshort = percentshort /
shortcounter * 100
'Change SHORTCOUNTER into the fraction of times short to
'number of replenishments made (COUNT = (approx.) TBO --
'this will reduce the variability due to TBO (e.g. a model
'with a TBO of 2 can havequite a few more shortages in a
'given time period than a model with a TBO of 10).
shortcounter = 100 * shortcounter / count
'Output results to 'DATA file in current directory.
OPEN "THESIS2.OUT" FOR APPEND AS #1
WRITE #1, dataset, datatype, variation, sigma / xbar, TBO,
          lotsize, 100 * (cost - k9) / k9, shortcounter,
          percentshort, 100 * (lotsizeforecasterror - mad)
          / mad, 100 * lotsizeforecasterror / xbar, 100 *
          lotsizetrackingsignal
CLOSE #1
'Note:  The 'DATA is given in percentages to provide
'non-exponential format in the output (in order to allow
'SAS to read the DATA directly (after the commas are
'removed)).
'Zero appropriate variables.
inventory = 0: production = 0: lotsizeforecasterror = 0:
```

```
lotsizetrackingsignal = 0
shortcounter = 0: percentshort = 0: cost = 0
ERASE lotdata
REDIM lotdata(n + horizon)
NEXT lotsize
NEXT TBO
NEXT dataset
END
'DATA statements

SUB forecaster
'This subroutine computes a focused forecast using Holt's
'exponential smoothing model and simple exponential
'smoothing (special case of Holt's model where gamma = 0).
DIM holt(4, 5, 6), bestholt(6), stat(n)
'Copy the demand 'DATA to a new matrix for the algorithm
'which smoothes out outliers
FOR i = 1 TO n: stat(i) = demand(i): NEXT i
'Store the various levels of Alpha and Gamma in the
'forecast matrix called HOLT
FOR j = 1 TO 4: FOR k = 1 TO 5: holt(j, k, 1) = j * .1:
NEXT k: NEXT j
FOR k = 1 TO 5: FOR j = 1 TO 4: holt(j, k, 2) = (1 - k) *
.1: NEXT j: NEXT k
w = .05   'Smoothing constant for the exponential smoothing
           form of MAD averagedemand = (demand(1) +
           demand(2)) / 2 'Initialize averge demand
'Compute the first forecast for all Alpha and Gamma levels
'as the average of the first two periods of demand.
FOR j = 1 TO 4
FOR k = 1 TO 5
holt(j, k, 3) = averagedemand
holt(j, k, 5) = ABS(holt(j, k, 3) - demand(3)) 'Initialize
individual MADs
NEXT k
NEXT j
'Begin forecast procedure
FOR h = 3 TO n   'Iterate through N periods
'Compute current average and std deviation of the demand
'sequence for H-1 periods
averagedemand = 0: sum = 0
FOR ij = 1 TO h - 1: sum = sum + stat(ij): NEXT ij
averagedemand = sum / (h - 1)
sumsquare = 0
FOR ik = 1 TO h - 1: sumsquare = sumsquare + (stat(ik) -
                                 averagedemand) ^ 2:
NEXT ik
deviation = (sumsquare / (h - 2)) ^ .5
bestholt(5) = 9999999999#   'Set high initial value of MAD
FOR j = 1 TO 4   'Iterate through all 4 Alpha levels
FOR k = 1 TO 5   'Iterate through all 5 Gamma levels
residual = demand(h) - holt(j, k, 3)    'Store difference
```

```
between last estimate
and actual demand
'Discount outliers (virtually all points should fall within
'3 or 4 std deviations if the points are distributed
'normally).
IF datatype = 1 THEN    'Only valid for constant and
slightly trending demand
    IF deviation > 0 THEN
        IF ABS(residual) / deviation > 4 THEN
            residuaL = SGN(residual) * 4 * deviation
            stat(h) = residual + averagedemand
        ELSE
        END IF
    ELSE
    END IF
ELSE
END IF
temp = holt(j, k, 3)    'Store last estimate (the one for
current period's
demand)
'Compute new estimate.
holt(j, k, 3) = (1 - holt(j, k, 1)) * (holt(j, k, 3) +
                holt(j, k, 4)) + holt(j, k, 1) * stat(h)
IF holt(j, k, 3) < 0 THEN holt(j, k, 3) = 0
'Compute new trend.
holt(j, k, 4) = (1 - holt(j, k, 2)) * holt(j, k, 4) +
                holt(j, k, 2) * (holt(j, k, 3) - temp)
'Compute current MAD and current smoothed forecast error.
holt(j, k, 5) = (1 - w) * (holt(j, k, 5)) + w *
ABS(residual)
holt(j, k, 6) = (1 - w) * (holt(j, k, 6)) + w * residual
'Determine the best forecast to date.
trackingsignal = holt(j, k, 6) / holt(j, k, 5)
'As defined by Silver and Peterson (1985)
'Note: A negatively biased forecast (i.e.,, where forecast
'exceeds demand) is preferable to a positively biased
'forecast  (i.e.,,  where  demand  exceeds forecast) since
being
'a few items overstock ("safety stock") is preferable to
'consistently being a few items short (causing too many
'premature setups).  [See EOQ example, Ibid.]
IF trackingsignal < .3 AND trackingsignal > -.9 THEN
    IF holt(j, k, 5) < bestholt(5) THEN
        bestholt(1) = holt(j, k, 1)
        'Alpha of best forecast for the period
        bestholt(2) = holt(j, k, 2)
        'Gamma of best forecast for the period
        bestholt(3) = holt(j, k, 3)
        'Best smoothed estimate
        bestholt(4) = holt(j, k, 4)
        'Best smoothed trend
        bestholt(5) = holt(j, k, 5)
```

```
        'Best MAD for the period
        bestholt(6) = holt(j, k, 6)
        'Best smoothed forecast error for the period
    ELSE
    END IF
ELSE
END IF
NEXT k     'Next Gamma
NEXT j     'Next Alpha
'Now store the best forecast for this period (which is the
'forecast  for  'demand  in period  H+1,   i.e.,   the next
period).
forecast(h + 1, 1) = INT(.5 + bestholt(3))
forecast(h + 1, 2) = INT(.5 + bestholt(4))
NEXT h     'Next period
'Compute the MAD for the entire forecast over N - Lastn
'periods.
mad = 0
FOR i = lastn + 1 TO n: mad = mad + ABS(forecast(i, 1) -
demand(i)): NEXT i
mad = mad / (n - lastn)
'Compute the tracking signal for the entire forecast over N
'- Lastn periods.
track = 0
FOR i = lastn + 1 TO n: track = track + demand(i) -
forecast(i, 1): NEXT i
trackingsignal = track / (mad * (n - lastn))
END SUB

SUB silvermeal
DIM trc(24), trcut(24)
trc(1) = 0: trcut(1) = 0: production = 0
trc(1) = setup: trcut(1) = trc(1)
FOR kk = 2 TO horizon
trc(kk) = trc(kk - 1) + (kk - 1) * D(kk) * holding
trcut(kk) = trc(kk) / kk
IF trcut(kk) > trcut(kk - 1) THEN 55
NEXT kk
55 FOR l = 1 TO kk - 1
production = production + D(l)
NEXT l
production = production - inventory
END SUB

SUB eisenhut  'part-period balancing
DIM trc(24), trcut(24)
trc(1) = 0: production = 0
FOR kk = 2 TO horizon
trc(kk) = trc(kk - 1) + (kk - 1) * D(kk) * holding
'determine first period where accumulated holding costs
'exceeds setup
IF trc(kk) > setup THEN
```

```
'determine which integer period is closer to actual setup
'costs
     IF ABS(trc(kk) - setup) > ABS(trc(kk - 1) - setup)
     THEN
          lastperiod = kk - 1
     ELSE
          lastperiod = kk
     END IF
     GOTO 565
ELSE 'continue to next period, i.e., next kk
END IF
NEXT kk
565 FOR l = 1 TO lastperiod
production = production + D(l)
NEXT l
production = production - inventory
END SUB

SUB eoq
production = 0: avg = 0
FOR i = 1 TO horizon
avg = avg + D(i)
NEXT i
avg = avg / horizon
production = (2 * avg * setup / holding) ^ .5 + short
production = INT(.5 + production) - inventory
END SUB

SUB tsado
production = 0: avg = 0
FOR i = 1 TO horizon
avg = avg + D(i)
NEXT i
avg = avg + short: avg = avg / horizon
time = lastn - 7
production = -avg * time + ((avg * time) ^ 2 + (2 * avg *
(cost + setup) /
holding)) ^ .5
production = INT(.5 + production) - inventory
END SUB

SUB wagnerwhitten
5 ERASE R, a, O
10 REDIM R(n), a(5000, 5), O(n)
60 m = n - lastn
110 FOR i = 1 TO m: R(i) = demand(i + 6): NEXT i
120 S = setup
130 C = holding
150 a(1, 1) = 1
160 a(1, 2) = 1
170 a(1, 3) = S
180 a(1, 4) = 0
```

```
190 a(1, 5) = 1
200 N1 = 0
210 N2 = 1
220 FOR i = 1 TO m
230 IF R(i) = 0 THEN 530
240 k9 = 999999999#
250 K8 = 0
260 FOR k = 1 TO N2
270 IF a(N1 + k, 3) > k9 THEN 320
280 K8 = N1 + k
290 k9 = a(K8, 3)
300 K7 = k9 + S
320 NEXT k
330 N3 = 1
340 j = N1 + N2
350 a(j + N3, 1) = i
360 a(j + N3, 2) = 1
370 a(j + N3, 3) = K7
380 a(j + N3, 4) = K8
390 a(j + N3, 5) = i
400 FOR k = 1 TO N2
410 C1 = (i - a(N1 + k, 5)) * C * R(i)
420 IF C1 > S THEN 500
430 IF a(N1 + k, 4) + C1 > K7 THEN 540
440 N3 = N3 + 1
450 a(j + N3, 1) = i
460 a(j + N3, 2) = 0
470 a(j + N3, 3) = a(N1 + k, 3) + C1
480 a(j + N3, 4) = N1 + k
490 a(j + N3, 5) = a(N1 + k, 5)
500 NEXT k
510 N1 = j
520 N2 = N3
530 NEXT i
540 k9 = 999999999#
550 K8 = 0
560 FOR k = 1 TO N2
570 IF a(N1 + k, 3) > k9 THEN 600
580 K8 = N1 + k
590 k9 = a(K8, 3)
600 NEXT k
610 'Solution Cost = k9
620 IF a(K8, 2) = 0 THEN 640
630 O(a(K8, 1)) = 1
640 K8 = a(K8, 4)
650 IF a(K8, 4) = 0 THEN 670
660 GOTO 620
670 FOR i = 1 TO m
680 IF i = 1 THEN 720
690 IF O(i) = 0 THEN 730
720 Q = 0
730 Q = Q + R(i)
```

```
740 NEXT i
END SUB

SUB wwheuristic
1105 ERASE R, a, O
1110 REDIM R(horizon), a(1000, 5), O(horizon)
1115 production = 0: flag = 0
1160 m = horizon
11110 FOR i = 1 TO m: R(i) = D(i): NEXT i
11120 S = setup
11130 C = holding
11150 a(1, 1) = 1
11160 a(1, 2) = 1
11170 a(1, 3) = S
11180 a(1, 4) = 0
11190 a(1, 5) = 1
11200 N1 = 0
11210 N2 = 1
11220 FOR i = 1 TO m
11230 IF R(i) = 0 THEN 11530
11240 k999 = 999999999#
11250 K8 = 0
11260 FOR k = 1 TO N2
11270 IF a(N1 + k, 3) > k999 THEN 11320
11280 K8 = N1 + k
11290 k999 = a(K8, 3)
11300 K7 = k999 + S
11320 NEXT k
11330 N3 = 1
11340 j = N1 + N2
11350 a(j + N3, 1) = i
11360 a(j + N3, 2) = 1
11370 a(j + N3, 3) = K7
11380 a(j + N3, 4) = K8
11390 a(j + N3, 5) = i
11400 FOR k = 1 TO N2
11410 C1 = (i - a(N1 + k, 5)) * C * R(i)
11420 IF C1 > S THEN 11500
11430 IF a(N1 + k, 4) + C1 > K7 THEN 11540
11440 N3 = N3 + 1
11450 a(j + N3, 1) = i
11460 a(j + N3, 2) = 0
11470 a(j + N3, 3) = a(N1 + k, 3) + C1
11480 a(j + N3, 4) = N1 + k
11490 a(j + N3, 5) = a(N1 + k, 5)
11500 NEXT k
11510 N1 = j
11520 N2 = N3
11530 NEXT i
11540 k999 = 999999999#
11550 K8 = 0
11560 FOR k = 1 TO N2
```

```
11570 IF a(N1 + k, 3) > k999 THEN 11600
11580 K8 = N1 + k
11590 k999 = a(K8, 3)
11600 NEXT k
11620 IF a(K8, 2) = 0 THEN 11640
11630 O(a(K8, 1)) = 1
11640 K8 = a(K8, 4)
11650 IF a(K8, 4) = 0 THEN 11670
11660 GOTO 11620
11670 FOR i = 1 TO m
11680 IF i = 1 THEN 11720
11690 IF O(i) = 0 THEN 11730
11705 IF flag = 1 THEN 11720
11706 production = Q
11707 flag = 1
11720 Q = 0
11730 Q = Q + R(i)
11740 NEXT i
11800 production = production - inventory
END SUB
```

APPENDIX D

ANOVA RESULTS -- GROUP I DATA

The following text provides the code used in the SAS routine. Output consists of all subsequent pages.

```
DATA;
INPUT SET TYPE VAR COFVAR TBO LOT COST SHORT
PERSHORT DELERR PERERR BIAS;
DROP COFVAR BIAS;
CARDS;
;
PROC ANOVA;
    CLASS SET TBO LOT VAR TYPE;
    MODEL COST SHORT PERSHORT DELERR PERERR =  LOT TBO
          TYPE VAR SET(TYPE VAR) LOT*TBO LOT*TYPE
          LOT*VAR LOT*SET(TYPE VAR) TBO*TYPE TBO*VAR
          TBO*SET(TYPE VAR) TYPE*VAR LOT*TBO*TYPE
          LOT*TBO*VAR LOT*TYPE*VAR TBO*TYPE*VAR
          LOT*TBO*TYPE*VAR;
    MEANS LOT TBO TYPE VAR LOT*TBO LOT*TYPE LOT*VAR
          TYPE*VAR TBO*TYPE TBO*VAR LOT*TBO*TYPE
          LOT*TBO*VAR LOT*TYPE*VAR LOT*TBO*TYPE*VAR
          / TUKEY;
    OUTPUT OUT=PLOTDATA P=YPRED R=YRESID;
PROC UNIVARIATE NORMAL PLOT;
    VAR YRESID;
PROC PLOT;
    PLOT YRESID*YPRED;
    PLOT YRESID*LOT;
    PLOT YRESID*TBO;
```

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ANALYSIS OF VARIANCE PROCEDURE

CLASS LEVEL INFORMATION

CLASS	LEVELS	VALUES
SET	36	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36
TBO	5	2 4 6 8 10
LOT	5	1 2 3 4 5
VAR	3	1 2 3
TYPE	2	0 1

NUMBER OF OBSERVATIONS IN DATA SET = 900

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ANALYSIS OF VARIANCE PROCEDURE

DEPENDENT VARIABLE: COST

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	403	3686092.21616365	9146.63080934	19.91	0.0001	0.941794	45.4268
ERROR	496	227810.79103130	459.29594966		ROOT MSE		COST MEAN
CORRECTED TOTAL	899	3913903.00719496			21.43119105		47.17739990

SOURCE	DF	ANOVA SS	F VALUE	PR > F
LOT	4	946113.07232383	514.98	0.0001
TBO	4	489507.17354140	266.44	0.0001
TYPE	1	0.03925625	0.00	0.9926
VAR	2	35043.05922935	38.15	0.0001
SET(VAR*TYPE)	31	50760.91525577	3.57	0.0001
TBO*LOT	16	1779305.47696152	242.12	0.0001
LOT*TYPE	4	1395.88338107	0.76	0.5516
LOT*VAR	8	10879.88607234	2.96	0.0030
SET*LOT(VAR*TYPE)	124	99400.84238123	1.75	0.0001
TBO*TYPE	4	1593.27970625	0.87	0.4834
TBO*VAR	8	15280.23991237	4.16	0.0001
SET*TBO(VAR*TYPE)	124	120365.34069452	2.11	0.0001
VAR*TYPE	1	2876.77084521	6.27	0.0126
TBO*LOT*TYPE	16	11624.15518830	1.58	0.0693
TBO*LOT*VAR	32	55271.14750878	3.76	0.0001
LOT*VAR*TYPE	4	13609.09291719	7.41	0.0001
TBO*VAR*TYPE	4	14383.25119396	7.83	0.0001
TBO*LOT*VAR*TYPE	16	38680.58979428	5.26	0.0001

ANALYSIS OF VARIANCE PROCEDURE

DEPENDENT VARIABLE: SHORT

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	403	171562.19431764	425.71264090	3.69	0.0001	0.749875	60.8570
ERROR	496	57225.64424587	115.37428275		ROOT MSE		SHORT MEAN
CORRECTED TOTAL	899	228787.83856351			10.74124214		17.64706882

SOURCE	DF	ANOVA SS	F VALUE	PR > F
LOT	4	30486.16966873	66.06	0.0001
TBO	4	16043.04983266	34.76	0.0001
TYPE	1	123.79601407	1.07	0.3006
VAR	2	18576.10674108	80.50	0.0001
SET(VAR*TYPE)	31	15079.47319543	4.22	0.0001
TBO*LOT	16	20314.03800492	11.00	0.0001
LOT*TYPE	4	452.24153184	0.98	0.4180
LOT*VAR	8	1813.96973241	1.97	0.0489
SET*LOT(VAR*TYPE)	124	31586.41024663	2.21	0.0001
TBO*TYPE	4	496.61755651	1.08	0.3676
TBO*VAR	8	6062.27799441	6.57	0.0001
SET*TBO(VAR*TYPE)	124	20598.03604712	1.44	0.0036
VAR*TYPE	1	1266.66733900	10.98	0.0010
TBO*LOT*TYPE	16	1146.31753691	0.62	0.8679
TBO*LOT*VAR	32	4291.18255354	1.16	0.2513
LOT*VAR*TYPE	4	672.33412621	1.46	0.2142
TBO*VAR*TYPE	4	992.90221677	2.15	0.0734
TBO*LOT*VAR*TYPE	16	1560.38197941	0.85	0.6336

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ANALYSIS OF VARIANCE PROCEDURE

DEPENDENT VARIABLE: PERSHORT

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	403	281450.71276121	698.38886541	3.02	0.0001	0.710690	57.8525
ERROR	496	114574.00837792	230.99598463		ROOT MSE		PERSHORT MEAN
CORRECTED TOTAL	899	396024.72113913			15.19855206		26.27121767

SOURCE	DF	ANOVA SS	F VALUE	PR > F
LOT	4	20555.52434800	22.25	0.0001
TBO	4	4602.89351921	4.98	0.0006
TYPE	1	7877.58638459	34.10	0.0001
VAR	2	52003.93702268	112.56	0.0001
SET(VAR*TYPE)	31	38944.01134356	5.44	0.0001
TBO*LOT	16	20308.04938346	5.49	0.0001
LOT*TYPE	4	633.97679372	0.69	0.6018
LOT*VAR	8	3068.40358821	1.66	0.1056
SET*LOT(VAR*TYPE)	124	43655.58215600	1.52	0.0009
TBO*TYPE	4	1129.23150214	1.22	0.3004
TBO*VAR	8	5343.82861746	2.89	0.0037
SET*TBO(VAR*TYPE)	124	70060.39072504	2.45	0.0001
VAR*TYPE	1	0.00000000	0.00	1.0000
TBO*LOT*TYPE	16	3305.08393570	0.89	0.5761
TBO*LOT*VAR	32	6903.08742218	0.93	0.5739
LOT*VAR*TYPE	4	399.68928756	0.43	0.7851
TBO*VAR*TYPE	4	4700.95904523	5.09	0.0005
TBO*LOT*VAR*TYPE	16	3713.60679959	1.00	0.4499

ANALYSIS OF VARIANCE PROCEDURE

DEPENDENT VARIABLE: DELERR

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	403	439079.22330910	1089.52660871	6.07	0.0001	0.831379	80.8649
ERROR	496	89054.58284487	179.54552993		ROOT MSE		DELERR MEAN
CORRECTED TOTAL	899	528133.80615397			13.39946006		16.57018464

SOURCE	DF	ANOVA SS	F VALUE	PR > F
LOT	4	1306.58413127	1.82	0.1238
TBO	4	91306.18279499	127.14	0.0001
TYPE	1	1947.09912491	10.84	0.0011
VAR	2	2051.15696855	5.71	0.0035
SET(VAR*TYPE)	31	141211.50848509	25.37	0.0001
TBO*LOT	16	3300.41726441	1.15	0.3065
LOT*TYPE	4	1552.03821285	2.16	0.0723
LOT*VAR	8	1786.05613204	1.24	0.2715
SET*LOT(VAR*TYPE)	124	39328.33911734	1.77	0.0001
TBO*TYPE	4	1444.48697099	2.01	0.0917
TBO*VAR	8	9039.00529322	6.29	0.0001
SET*TBO(VAR*TYPE)	124	85304.65735091	3.83	0.0001
VAR*TYPE	1	28915.72348101	161.05	0.0001
TBO*LOT*TYPE	16	4459.82212702	1.55	0.0776
TBO*LOT*VAR	32	6196.29569467	1.08	0.3553
LOT*VAR*TYPE	4	216.24212907	0.30	0.8772
TBO*VAR*TYPE	4	20702.15150609	28.83	0.0001
TBO*LOT*VAR*TYPE	16	0.00000000	0.00	1.0000

SAS [illegible] WEDNESDAY, APRIL 19, 1989 [illegible]

ANALYSIS OF VARIANCE PROCEDURE

DEPENDENT VARIABLE: PERERR

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	403	424949.80902476	1054.46602736	26.76	0.0001	0.956033	13.6995
ERROR	496	19543.05698010	39.40132456		ROOT MSE		PERERR MEAN
CORRECTED TOTAL	899	444492.86600486			6.27704744		45.81955531

SOURCE	DF	ANOVA SS	F VALUE	PR > F
LOT	4	234.71011152	1.49	0.2042
TBO	4	12250.02562361	77.73	0.0001
TYPE	1	12817.17504600	325.30	0.0001
VAR	2	219300.40495487	2782.91	0.0001
SET(VAR*TYPE)	31	158217.40130964	129.53	0.0001
TBO*LOT	16	841.88154835	1.34	0.1705
LOT*TYPE	4	226.87175761	1.44	0.2197
LOT*VAR	8	589.60354735	1.87	0.0625
SET*LOT(VAR*TYPE)	124	8082.94662557	1.65	0.0001
TBO*TYPE	4	32.95368533	0.21	0.9333
TBO*VAR	8	3465.19045606	10.99	0.0001
SET*TBO(VAR*TYPE)	124	14380.82704713	2.94	0.0001
VAR*TYPE	1	0.00000000	0.00	1.0000
TBO*LOT*TYPE	16	875.81329835	1.39	0.1416
TBO*LOT*VAR	32	3083.52190212	2.45	0.0001
LOT*VAR*TYPE	4	14.20115316	0.09	0.9855
TBO*VAR*TYPE	4	2455.22493057	15.58	0.0001
TBO*LOT*VAR*TYPE	16	0.00000000	0.00	1.0000

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ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: COST
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE.
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=496 MSE=459.296
CRITICAL VALUE OF STUDENTIZED RANGE=3.872
MINIMUM SIGNIFICANT DIFFERENCE=6.1851

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	LOT
A	110.333	180	5
B	45.125	180	1
C	29.362	180	3
C			
C	27.852	180	2
C			
C	23.415	180	4

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ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: SHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE.
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=496 MSE=115.374
CRITICAL VALUE OF STUDENTIZED RANGE=3.872
MINIMUM SIGNIFICANT DIFFERENCE=3.0999

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY	GROUPING	MEAN	N	LOT
	A	24.557	180	4
	A			
B	A	21.549	180	2
B				
B		19.866	180	3
	C	14.010	180	1
	D	8.253	180	5

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ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERSHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=496 MSE=230.996
CRITICAL VALUE OF STUDENTIZED RANGE=3.872
MINIMUM SIGNIFICANT DIFFERENCE=4.3863

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING		MEAN	N	LOT
	A	32.814	180	4
	A			
B	A	29.191	180	2
B				
B	C	26.956	180	3
	C			
	C	23.535	180	1
	D	18.861	180	5

ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: DELERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=496 MSE=179.546
CRITICAL VALUE OF STUDENTIZED RANGE=3.872
MINIMUM SIGNIFICANT DIFFERENCE=3.8671

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	LOT
A	18.223	180	4
A			
A	17.490	180	2
A			
A	16.421	180	1
A			
A	15.960	180	5
A			
A	14.757	180	3

```
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          ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

        ALPHA=0.05  DF=496  MSE=39.4013
        CRITICAL VALUE OF STUDENTIZED RANGE=3.872
        MINIMUM SIGNIFICANT DIFFERENCE=1.8116

 MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

      TUKEY   GROUPING            MEAN      N  LOT

                     A         46.2984    180  2
                     A
                     A         46.2767    180  4
                     A
                     A         45.9421    180  5
                     A
                     A         45.6713    180  1
                     A
                     A         44.9093    180  3
```

ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: COST
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=496 MSE=459.296
CRITICAL VALUE OF STUDENTIZED RANGE=3.872
MINIMUM SIGNIFICANT DIFFERENCE=6.1851

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	TBO
A	91.932	180	10
B	45.206	180	8
B			
B	41.132	180	2
C	29.591	180	6
C			
C	28.025	180	4

ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: SHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=496 MSE=115.374
CRITICAL VALUE OF STUDENTIZED RANGE=3.872
MINIMUM SIGNIFICANT DIFFERENCE=3.0999

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	TBO
A	23.075	180	10
B	19.616	180	8
B			
B	18.610	180	6
B			
B	16.622	180	4
C	10.312	180	2

```
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              ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERSHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

       ALPHA=0.05  DF=496  MSE=230.996
       CRITICAL VALUE OF STUDENTIZED RANGE=3.872
       MINIMUM SIGNIFICANT DIFFERENCE=4.3863

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

     TUKEY   GROUPING            MEAN      N  TBO

                    A          30.023    180  10
                    A
             B      A          27.601    180  4
             B
             B                 25.440    180  2
             B
             B                 24.211    180  6
             B
             B                 24.082    180  8
```

ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: DELERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE.
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=406 MSE=179.546
CRITICAL VALUE OF STUDENTIZED RANGE=3.872
MINIMUM SIGNIFICANT DIFFERENCE=3.8671

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	TBO
A	29.589	180	10
B	25.408	180	8
C	16.538	180	6
D	8.938	180	4
E	2.376	180	2

```
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               ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE.
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

        ALPHA=0.05  DF=496  MSE=39.4013
        CRITICAL VALUE OF STUDENTIZED RANGE=3.872
        MINIMUM SIGNIFICANT DIFFERENCE=1.8116

 MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

      TUKEY   GROUPING            MEAN      N  TBO

                   A            49.9441   180  10
                   A
                   A            49.4533   180  8

                   B            46.2755   180  6

                   C            43.1080   180  4

                   D            40.3169   180  2
```

```
                    ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: COST
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

        ALPHA=0.05  DF=496  MSE=459.296
        CRITICAL VALUE OF STUDENTIZED RANGE=2.779
        MINIMUM SIGNIFICANT DIFFERENCE=2.9221

       WARNING: CELL SIZES ARE NOT EQUAL.
                HARMONIC MEAN OF CELL SIZES=415.278

 MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

       TUKEY   GROUPING            MEAN      N  TYPE

                      A          47.182    575  0
                      A
                      A          47.169    325  1
```

ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: SHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=496 MSE=115.374
CRITICAL VALUE OF STUDENTIZED RANGE=2.779
MINIMUM SIGNIFICANT DIFFERENCE = 4646

WARNING: CELL SIZES ARE NOT EQUAL.
HARMONIC MEAN OF CELL SIZES=415.278

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	TYPE
A	17.9250	575	0
A			
A	17.1538	325	1

```
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              ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERSHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

        ALPHA=0.05  DF=496  MSE=230.996
        CRITICAL VALUE OF STUDENTIZED RANGE=2.779
        MINIMUM SIGNIFICANT DIFFERENCE=2.0723

       WARNING: CELL SIZES ARE NOT EQUAL.
                HARMONIC MEAN OF CELL SIZES=415.278

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

      TUKEY    GROUPING             MEAN       N  TYPE

                    A             28.495     575  0

                    B             22.336     325  1
```

```
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           ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: DELERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

        ALPHA=0.05  DF=496  MSE=179.546
        CRITICAL VALUE OF STUDENTIZED RANGE=2.779
        MINIMUM SIGNIFICANT DIFFERENCE=1.827

       WARNING: CELL SIZES ARE NOT EQUAL.
                HARMONIC MEAN OF CELL SIZES=415.278

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

      TUKEY   GROUPING           MEAN      N  TYPE

                 A             18.5266   325  1

                 B             15.4644   575  0
```

ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=496 MSE=39.4013
CRITICAL VALUE OF STUDENTIZED RANGE=2.779
MINIMUM SIGNIFICANT DIFFERENCE=.85587

WARNING: CELL SIZES ARE NOT EQUAL.
HARMONIC MEAN OF CELL SIZES=415.278

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	TYPE
A	46.6567	575	0
B	40.8000	325	1

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ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: COST
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE

ALPHA=0.05 CONFIDENCE=0.95 DF=496 MSE=459.296
CRITICAL VALUE OF STUDENTIZED RANGE=3.325

COMPARISONS SIGNIFICANT AT THE 0.05 LEVEL ARE INDICATED BY '***'

VAR COMPARISON	SIMULTANEOUS LOWER CONFIDENCE LIMIT	DIFFERENCE BETWEEN MEANS	SIMULTANEOUS UPPER CONFIDENCE LIMIT	
3 - 2	8.932	14.367	19.802	***
3 - 1	13.664	18.702	23.740	***
2 - 3	-19.802	-14.367	-8.932	***
2 - 1	0.553	4.335	8.117	***
1 - 3	-23.740	-18.702	-13.664	***
1 - 2	-8.117	-4.335	-0.553	***

ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: SHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE

ALPHA=0.05 CONFIDENCE=0.95 DF=496 MSE=115.374
CRITICAL VALUE OF STUDENTIZED RANGE=3.325

COMPARISONS SIGNIFICANT AT THE 0.05 LEVEL ARE INDICATED BY '***'

VAR COMPARISON	SIMULTANEOUS LOWER CONFIDENCE LIMIT	DIFFERENCE BETWEEN MEANS	SIMULTANEOUS UPPER CONFIDENCE LIMIT	
3 - 2	6.2910	9.0148	11.7387	***
3 - 1	10.8952	13.4202	15.9453	***
2 - 3	-11.7387	-9.0148	-6.2910	***
2 - 1	2.5097	4.4054	6.3011	***
1 - 3	-15.9453	-13.4202	-10.8952	***
1 - 2	-6.3011	-4.4054	-2.5097	***

ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERSHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE

ALPHA=0.05 CONFIDENCE=0.95 DF=496 MSE=230.996
CRITICAL VALUE OF STUDENTIZED RANGE=3.325

COMPARISONS SIGNIFICANT AT THE 0.05 LEVEL ARE INDICATED BY '***'

VAR COMPARISON	SIMULTANEOUS LOWER CONFIDENCE LIMIT	DIFFERENCE BETWEEN MEANS	SIMULTANEOUS UPPER CONFIDENCE LIMIT	
3 - 2	11.4351	15.2893	19.1434	***
3 - 1	18.9225	22.4954	26.0683	***
2 - 3	-19.1434	-15.2893	-11.4351	***
2 - 1	4.5238	7.2062	9.8885	***
1 - 3	-26.0683	-22.4954	-18.9225	***
1 - 2	-9.8885	-7.2062	-4.5238	***

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ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: DELERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE

ALPHA=0.05 CONFIDENCE=0.95 DF=496 MSE=179.546
CRITICAL VALUE OF STUDENTIZED RANGE=3.325

COMPARISONS SIGNIFICANT AT THE 0.05 LEVEL ARE INDICATED BY '***'

VAR COMPARISON	SIMULTANEOUS LOWER CONFIDENCE LIMIT	DIFFERENCE BETWEEN MEANS	SIMULTANEOUS UPPER CONFIDENCE LIMIT	
3 - 2	0.7936	4.1915	7.5895	***
3 - 1	1.2925	4.4424	7.5924	***
2 - 3	-7.5895	-4.1915	-0.7936	***
2 - 1	-2.1140	0.2509	2.6157	
1 - 3	-7.5924	-4.4424	-1.2925	***
1 - 2	-2.6157	-0.2509	2.1140	

ANALYSIS OF VARIANCE PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE

ALPHA=0.05 CONFIDENCE=0.95 DF=496 MSE=39.4013
CRITICAL VALUE OF STUDENTIZED RANGE=3.325

COMPARISONS SIGNIFICANT AT THE 0.05 LEVEL ARE INDICATED BY '***'

VAR COMPARISON	SIMULTANEOUS LOWER CONFIDENCE LIMIT	DIFFERENCE BETWEEN MEANS	SIMULTANEOUS UPPER CONFIDENCE LIMIT	
3 - 2	32.3538	33.9455	35.5373	***
3 - 1	45.1264	46.6020	48.0777	***
2 - 3	-35.5373	-33.9455	-32.3538	***
2 - 1	11.5487	12.6565	13.7643	***
1 - 3	-48.0777	-46.6020	-45.1264	***
1 - 2	-13.7643	-12.6565	-11.5487	***

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ANALYSIS OF VARIANCE PROCEDURE

MEANS

TBO	LOT	N	COST	SHORT	PERSHORT	DELERR	PERERR
2	1	36	38.351292	11.5868706	27.6259877	3.1506861	40.7559350
2	2	36	45.068724	8.2236813	21.6130518	1.4916322	40.0517133
2	3	36	41.637696	11.6952362	25.6801953	3.4516604	40.6816926
2	4	36	39.587900	10.9064994	26.2499059	1.3991551	39.7407972
2	5	36	41.015926	9.1463710	24.0292803	2.4092840	40.3542586
4	1	36	29.613956	12.7320075	23.1297416	10.4183065	43.7647575
4	2	36	29.166954	16.6790863	28.[illegible]220669	9.2017270	43.5987844
4	3	36	25.669043	18.3874992	32.4658052	8.4512364	42.7057975
4	4	36	23.110066	20.9525984	29.2517025	10.2022562	43.3855681
4	5	36	32.546886	14.3588956	24.6356298	6.4141020	42.0640456
6	1	36	36.870735	14.0920904	17.7349140	15.8985332	45.5631914
6	2	36	23.613733	22.6783861	26.5706706	17.5875421	47.4626722
6	3	36	24.535388	16.6623167	23.6179099	15.4453788	45.6573100
6	4	36	19.666236	26.1518947	32.3546905	20.9582918	47.8711169
6	5	36	43.268506	11.4764432	20.7745366	12.8003435	44.8034000
8	1	36	46.045366	15.2266611	18.2628241	22.5282606	47.5732508
8	2	36	22.264563	25.8883553	31.6475554	28.1698494	50.2491919
8	3	36	27.933226	21.2623257	21.3731321	23.0071438	48.6396100
8	4	36	18.449472	29.8533942	31.7745999	25.7930292	49.8674569
8	5	36	111.319441	5.7497322	17.3331541	27.5418358	50.9367650
10	1	36	74.741926	16.4237752	30.8013930	30.1110295	50.6991947
10	2	36	19.104296	34.1762861	37.6002202	31.0091163	50.1097353
10	3	36	27.032730	29.3212882	31.6428206	23.4282865	46.8509411
10	4	36	15.263387	34.9206342	42.4376674	32.7597800	50.5187253
10	5	36	323.516550	0.5343915	7.5319663	30.6361549	51.5319711

LOT	TYPE	N	COST	SHORT	PERSHORT	DELERR	PERERR
1	0	115	43.279024	14.8156586	25.5573693	15.2574145	48.5217337
1	1	65	48.390002	12.5853821	19.9563308	18.4806570	40.6281306
2	0	115	28.078392	21.7194675	31.2755397	16.5895387	49.2944903
2	1	65	26.896655	21.2478440	25.5021844	19.0830507	40.9976786
3	0	115	29.588842	20.3116904	30.2502503	13.2843806	47.5009052
3	1	65	26.960157	19.0767320	21.1276352	17.3616836	40.3240700
4	0	115	24.063509	23.8606455	34.1635841	15.6983463	48.5919562
4	1	65	22.268779	25.7890233	30.4254802	22.6883172	42.1805686
5	0	115	110.902058	8.9220331	21.2305819	16.4921929	49.3744530
5	1	65	109.327483	7.0697877	14.6684231	15.0193806	39.8694423

LOT	VAR	N	COST	SHORT	PERSHORT	DELERR	PERERR
1	1	100	36.940171	10.4391340	16.2916460	15.5498420	35.2260771
1	2	55	46.878455	17.0631200	26.2697320	17.5844117	48.8791469
1	3	25	74.004228	21.5786230	46.4903644	17.3487409	80.3946828
2	1	100	25.861790	17.9259780	24.3463727	15.9092832	35.4119569
2	2	55	26.914943	21.7685711	32.1724424	17.7196345	49.0620858
2	3	25	36.431874	35.5591764	42.0082980	23.3074812	83.7642036
3	1	100	26.524868	16.5054686	21.9655850	14.6556359	35.0566523
3	2	55	28.353247	19.7504256	27.7688521	14.2901070	47.2847678
3	3	25	42.928468	33.5604684	45.1291880	16.1877489	79.0936476

ANALYSIS OF VARIANCE PROCEDURE

MEANS

LOT	VAR	N	COST	SHORT	PERSHORT	DELERR	PERERR
4	1	100	21.735546	21.1604829	29.5038136	19.0856953	36.5013258
4	2	55	23.188197	26.2467084	32.7371812	15.1561776	47.6476620
4	3	25	30.634749	34.4257400	46.2216824	21.5156456	82.3623172
5	1	100	105.214565	6.1542218	12.6174229	14.1821535	35.2019325
5	2	55	112.616491	9.3834076	21.8074668	15.8866886	47.8077382
5	3	25	125.786387	14.1624164	37.3524583	23.2351481	84.7942800

VAR	TYPE	N	COST	SHORT	PERSHORT	DELERR	PERERR
1	0	300	41.5524285	14.3540646	21.1855728	10.4873319	34.3959300
1	1	200	45.8098269	14.5615458	20.5840610	23.9603071	37.1055773
2	0	150	46.1299251	16.7934131	30.6611387	21.3729779	49.3239977
2	1	125	49.3426766	21.3012867	25.1391303	9.8327150	46.7110191
3	0	125	61.9571411	27.8572848	43.4403982	20.3169529	82.0818262

TBO	TYPE	N	COST	SHORT	PERSHORT	DELERR	PERERR
2	0	115	42.3513970	10.8285809	28.9436864	2.7901226	43.0536959
2	1	65	38.9754576	9.3973062	19.2402957	1.6501992	35.4748194
4	0	115	29.7264624	16.6363644	29.4172402	8.3031069	45.8324544
4	1	65	26.7850057	16.5966343	24.3870793	10.0599559	38.2877854
6	0	115	28.2918941	19.8282751	25.7796293	15.3237928	49.2387689
6	1	65	31.8891951	16.4552165	21.4344709	18.5801083	41.0328991
8	0	115	44.1466057	19.6975162	27.0009387	23.5829934	52.5085196
8	1	65	47.0814584	19.4720384	18.9184249	28.6369235	44.0476098
10	0	115	92.3954665	22.6387584	31.3356307	27.2618572	52.6499997
10	1	65	91.1119594	23.8475737	27.6997830	33.7059021	45.1567765

TBO	VAR	N	COST	SHORT	PERSHORT	DELERR	PERERR
2	1	100	41.338955	9.1807235	19.4537599	1.5167419	31.1304066
2	2	55	41.705217	11.1145868	25.8924474	2.3605642	42.7257675
2	3	25	39.045318	13.0694835	48.3873024	5.8648727	71.7632168
4	1	100	25.075949	13.2376394	19.5481367	7.9054686	33.1103388
4	2	55	27.766873	19.8395393	32.4704148	6.8527708	44.5124778
4	3	25	40.391826	23.0809814	49.0982516	17.6522148	80.0087260
6	1	100	25.800817	13.6145195	18.9985942	16.3633748	35.8238638
6	2	55	29.857509	19.5385737	25.3750704	12.4653855	46.6994500
6	3	25	45.404832	36.5506885	42.4963872	26.1963816	87.1496292
8	1	100	37.368998	14.5375112	19.5539612	22.7981010	37.5645954
8	2	55	47.106055	21.7146276	25.9460962	26.8921221	52.2590685
8	3	25	71.376865	35.3136490	38.0949660	32.5826985	90.8351032
10	1	100	86.692220	21.6148917	27.1703881	30.7989257	39.7697400
10	2	55	91.715679	22.0049053	31.0716458	32.0661768	54.4846369
10	3	25	113.368865	31.2716217	39.1250839	19.2985970	80.6524560

ANALYSIS OF VARIANCE PROCEDURE

MEANS

TBO	LOT	TYPE	N	COST	SHORT	PERSHORT	DELERR	PERERR
2	1	0	23	41.371647	11.5563140	31.7391568	3.5406620	43.5479783
2	1	1	13	33.007586	11.6409322	20.3488423	2.4607285	35.8161662
2	2	0	23	43.744716	9.4864454	25.0289427	2.5149629	43.0366178
2	2	1	13	47.411202	5.9895602	15.5695525	-0.3465582	34 7707285
2	3	0	23	43.765682	12.4505865	29.5076300	4.2145021	43.5141865
2	3	1	13	37.872799	10.3588473	18.9085800	2.1020174	35.6703577
2	4	0	23	39.524319	10.8152763	31.7050638	0.8082994	42.0697304
2	4	1	13	39 700390	11.0678942	22.1368988	2.4445151	35.6203769
2	5	0	23	43.350622	9.8342823	26.7376187	2.8721863	43.0999665
2	5	1	13	36.885311	7.9292972	19.2376048	1.5903031	35.4964677
4	1	0	23	30.031955	13.0889958	25 6954937	9.7516646	46.4335365
4	1	1	13	28.874418	12.1004129	18.5875648	11.5977498	39.0430715
4	2	0	23	30.398780	17.6419880	31.7427596	9.6020431	46.9429130
4	2	1	13	27.042955	14.9754911	22.8239738	8.4934780	37.6822477
4	3	0	23	26.257756	17.2402766	35.3208377	7.3350028	45.2473374
4	3	1	13	24.627475	20.4172008	27.4145939	10.4260946	38.2119962
4	4	0	23	24.279529	20.8913361	27.8439374	8.8673622	45.7579483
4	4	1	13	21.041015	21.0609856	31.7423638	12.5639917	39.1882800
4	5	0	23	32.664293	14.3192257	26.4831727	5.9594618	44.7805361
4	5	1	13	32.339166	14.4290809	21.3669000	7.2184655	37.3133315
6	1	0	23	34.459644	17.6915107	20.0851703	14.1850922	48.1662730
6	1	1	13	41.118918	7.6961928	13.5767681	18.9300056	40.9577392
6	2	0	23	23.818962	22.9889191	24.6012409	19.1336590	51.8602196
6	2	1	13	23.250635	22.1289815	30.0550462	14.8521044	39.7377808
6	3	0	23	24.625088	19.4927530	28.3521514	13.9059178	49.2983648
6	3	1	13	24.376688	17.1930831	15.2419442	18.1690405	40.9846746
6	4	0	23	20.361613	26.1991013	32.9974873	18.6926481	50.3358987
6	4	1	13	18.435953	26.0683754	31.2351270	24.0667382	43.5103492
6	5	0	23	38.184163	12.7690915	22.8720964	11.0016469	47.5330683
6	5	1	13	52.263881	9.1894499	17.0634691	15.9826528	39.9730515
8	1	0	23	42.787957	15.4632644	21.1513441	18.1724037	49.4641078
8	1	1	13	51.808476	14.8080553	13.2077504	30.2347766	44.2278885
8	2	0	23	23.550808	24.2977909	34.9526161	24.7710207	52.6125083
8	2	1	13	20.044284	26.9793538	25.8001403	34.1831616	46.0679400
8	3	0	23	28.140454	22.4778847	25.0834655	23.1329235	52.2972861
8	3	1	13	27.566591	19.1117215	14.8086962	22.7846106	42.1683369
8	4	0	23	18.958649	29.2236013	32.4408209	22.3015001	52.7158009
8	4	1	13	17.548620	30.9676431	30.5959012	31.9703496	44.8280792
8	5	0	23	107.295161	7.0250400	21.3764468	29.5371192	55 4533948
8	5	1	13	118.439321	3.4934184	10.1796363	24.0117191	42.9458046
10	1	0	23	67.733916	16.2782080	29.1156817	30.6372498	54.9967726
10	1	1	13	87.140712	16.6813172	34.0607282	29.1800243	43.0957877
10	2	0	23	18.878698	34.1821943	40.0521393	26.9260077	52.0201922
10	2	1	13	16.734202	34.1658331	33.2622095	38.2330777	46.7296962
10	3	0	23	25.155230	29.8969513	32.9871669	17.8335566	48.1473513
10	3	1	13	30.357230	28.3028073	29.2643617	33.3266547	44.5849846
10	4	0	23	17.193436	32.1739126	45.8405912	27.8219217	52.0804026
10	4	1	13	14.617915	39.7802185	36 4171100	41.4959911	47 7557577
10	5	0	23	333.016052	0 6605259	8 6835747	33.0905504	56.0052796
10	5	1	13	306 709738	0.3076923	5.4945054	26.2937626	43.6176562

ANALYSIS OF VARIANCE PROCEDURE

MEANS

TBO	LOT	VAR	N	COST	SHORT	PERSHORT	DELERR	PERERR
2	1	1	20	35.652615	10.2024193	20.7079948	1.1681634	30.9969555
2	1	2	11	41.800691	14.0612902	27.3707455	4.4870651	43.5607145
2	1	3	5	41.557320	11.6809524	55.8594920	8.1407430	73.6213380
2	2	1	20	47.600213	6.9913958	16.7696575	0.0231525	30.6992040
2	2	2	11	44.792258	7.9692475	22.2167776	2.1314900	42.5986500
2	2	3	5	35.550996	13.7125778	39.6584320	5.8858642	71.8584680
2	3	1	20	41.004741	10.6719642	21.0029491	3.2649689	31.6641095
2	3	2	11	41.565353	11.8368609	24.7918253	2.5342203	42.8284255
2	3	3	5	44.328674	15.4787500	46.3435940	6.2171946	72.0292140
2	4	1	20	41.729544	10.2501397	21.4077739	1.3324289	31.0406510
2	4	2	11	40.188849	11.5074367	29.5219966	0.5750652	41.9735809
2	4	3	5	29.699238	12.2098760	52.8198340	3.4790574	69.6292580
2	5	1	20	40.707662	7.7876983	17.3804241	1.7950959	31.2511130
2	5	2	11	40.178935	10.1980985	25.5608918	2.0749805	42.6674584
2	5	3	5	44.090362	12.2672614	47.2551600	5.6015044	71.6778060
4	1	1	20	26.358100	8.0779718	12.1702713	9.4642635	33.6553610
4	1	2	11	27.986749	18.9340963	25.5925355	8.6225463	45.5071055
4	1	3	5	46.217230	17.7035550	61.5422760	18.1851506	80.3691780
4	2	1	20	26.158653	13.5376664	20.2139254	6.9514014	32.7959850
4	2	2	11	29.261732	18.8107735	35.9808564	6.1691523	44.5734627
4	2	3	5	41.135646	24.5550540	45.3454400	24.9747004	84.5656900
4	3	1	20	23.236008	16.2989216	24.3073828	7.8872785	33.0090885
4	3	2	11	25.979820	18.1165683	40.8742818	6.6660872	44.1587055
4	3	3	5	34.717476	27.3378580	46.6008460	14.6343534	78.3034360
4	4	1	20	20.680239	17.2189433	25.6360427	10.0307107	33.6315635
4	4	2	11	22.605149	26.1005670	28.5626696	7.5211353	44.6306436
4	4	3	5	33.940186	24.5616880	45.2302140	16.7869040	78.8624200
4	5	1	20	28.946743	11.0546938	15.4130612	5.1936790	32.2596960
4	5	2	11	33.000916	17.2356915	31.3417308	5.2849331	43.6924718
4	5	3	5	45.948590	21.2467518	46.7724820	13.7799658	77.8429060
6	1	1	20	31.985145	10.0039677	12.7921809	17.4798021	36.1200145
6	1	2	11	37.846075	11.3177226	20.5430114	12.0525151	46.2744445
6	1	3	5	54.287344	36.4761900	31.3260520	18.0346978	81.7711420
6	2	1	20	20.555307	15.5088375	22.5390190	15.2738412	35.5405940
6	2	2	11	21.805482	26.4784209	24.6995645	10.9754949	46.2545855
6	2	3	5	39.825586	42.9965040	46.8137100	41.3888492	97.9527760
6	3	1	20	21.721764	13.8977265	19.2675513	16.7133733	36.0313805
6	3	2	11	23.262272	18.1601718	19.8243564	10.3068960	45.7837164
6	3	3	5	38.590740	38.8253960	49.3651620	21.6780630	83.8829340
6	4	1	20	17.067885	21.5138880	27.7656258	20.9123176	37.3547355
6	4	2	11	18.683298	28.0303018	36.3856848	17.5058669	48.7086627
6	4	3	5	32.222102	40.5714260	41.8427620	28.7375228	88.0940420
6	5	1	20	36.673983	7.1481777	12.6285942	11.4375395	34.0725945
6	5	2	11	46.690417	13.7062515	25.4218347	11.4861544	46.4758409
6	5	3	5	62.118390	23.8839264	43.1342500	21.1427754	84.0472520
8	1	1	20	43.284639	7.9271843	9.8315352	20.8647086	38.5985290
8	1	2	11	38.398189	21.9303420	21.7263349	28.2682978	53.0412682
8	1	3	5	73.912066	29.6764706	44.5122560	17.3543864	79.4425000
8	2	1	20	18.803469	21.0984845	28.6597792	26.0557278	38.3990800
8	2	2	11	21.285856	26.1904755	35.4075536	30.4870403	54.1605227
8	2	3	5	38.406094	45.1031740	35.3266640	31.5285156	89.0447120
8	3	1	20	23.895520	14.9523810	14.2323318	20.1253095	36.7727260

ANALYSIS OF VARIANCE PROCEDURE

MEANS

TBO	LOT	VAR	N	COST	SHORT	PERSHORT	DELERR	PERERR
8	3	2	11	27.546029	20.2922079	26.2901736	23.0844005	50.4077764
8	3	3	5	44.935882	48.6363640	39.1188420	34.3645163	92.2171800
8	4	1	20	15.895039	24.2956340	32.8275536	24.5120144	38.0240930
8	4	2	11	17.873941	34.6861464	27.1692995	22.1681112	50.3316236
8	4	3	5	29.933370	41.4523800	37.6944460	38.8919077	96.2197460
8	5	1	20	85.966324	4.4138723	12.2186063	22.6327446	38.0285490
8	5	2	11	130.426257	5.4739664	16.1371193	30.4527605	53.3541518
8	5	3	5	170.695612	11.6999564	33.8226220	40.7741663	97.2513780
10	1	1	20	47.420356	15.9841267	25.9562478	28.9722724	38.7595255
10	1	2	11	88.360573	19.0721491	36.1151327	34.4916344	56.0122018
10	1	3	5	154.067180	12.3559468	39.2117460	25.0287268	86.7692560
10	2	1	20	16.191307	32.4935060	33.5494823	31.2422929	39.6249215
10	2	2	11	17.429388	29.3939382	42.5574600	38.8349952	57.7231982
10	2	3	5	27.241050	51.4285720	42.8972440	12.8594764	75.2993720
10	3	1	20	22.766305	26.7063497	31.0177101	25.2873494	37.8059570
10	3	2	11	23.412759	30.3463191	27.0636235	26.8589308	53.2452155
10	3	3	5	52.069566	37.5259740	44.2174960	4.0446172	69.0354740
10	4	1	20	13.305022	32.5238095	39.8820718	38.6410049	42.2555860
10	4	2	11	16.589749	30.9090900	42.0462555	28.0107093	52.5937991
10	4	3	5	27.378848	53.3333300	53.5211560	19.6828360	79.0061200
10	5	1	20	333.778110	0.3666666	5.4464285	29.8517086	40.4027100
10	5	2	11	312.785927	0.3030303	7.5757573	30.1346145	52.8487700
10	5	3	5	306.077680	1.7142858	15.7777774	34.8773286	93.1520580

LOT	VAR	TYPE	N	COST	SHORT	PERSHORT	DELERR	PERERR
1	1	0	60	30.853670	11.5792636	16.2729969	10.8061813	34.4807863
1	1	1	40	46.069923	8.7289396	16.3196196	22.6653331	36.3440132
1	2	0	30	42.525395	15.6526450	26.6819516	22.4171087	50.0428373
1	2	1	25	52.102128	18.7556900	25.7750685	11.7851753	47.4827184
1	3	0	25	74.004228	21.5786230	46.4903644	17.3487409	80.3946828
2	1	0	60	23.700616	17.5461594	25.2176700	9.9437386	34.0533748
2	1	1	40	29.103552	18.4957060	23.0394267	24.8576000	37.4498300
2	2	0	30	29.872711	18.5329932	34.4473138	24.2828534	51.0519603
2	2	1	25	23.365622	25.6512646	29.4425968	9.6437718	46.6742364
2	3	0	25	36.431874	35.5591764	42.0082980	23.3074812	83.7642036
3	1	0	60	23.266741	16.2201810	22.8273606	9.5955491	34.1374246
3	1	1	40	31.412057	16.9334001	20.6728918	22.2457661	36.4354935
3	2	0	30	31.116688	17.4540610	32.6968750	18.2425698	47.9005807
3	2	1	25	25.037116	22.5060631	21.8552247	9.5471515	46.5457924
3	3	0	25	42.928468	33.5604684	45.1291880	16.1877489	79.0936476
4	1	0	60	21.357070	19.1981219	28.5435471	11.6339871	34.7499730
4	1	1	40	22.303260	24.1040244	30.9442133	30.2632577	39.1283550
4	2	0	30	24.000355	24.3814473	35.3552429	18.9793152	48.1339550
4	2	1	25	22.213608	26.4850217	29.5955072	10.5684124	47.0641104
4	3	0	25	30.634749	34.4257400	46.2216824	21.5156456	82.3623172
5	1	0	60	108.584046	7.2265970	13.0662691	10.4572035	34.5580908
5	1	1	40	100.160343	4.5456589	11.9441535	19.7695785	36.1701950
5	2	0	30	103.134476	7.9459191	24.1243104	22.9430425	49.4906550
5	2	1	25	123.994909	11.1083939	19.0272545	7.4190640	45.7882380
5	3	0	25	125.786387	14.1624164	37.3524583	23.2351481	84.7942800

ANALYSIS OF VARIANCE PROCEDURE

MEANS

TBO	LOT	VAR	TYPE	N	COST	SHORT	PERSHORT	DELERR	PERERR
2	1	1	0	12	39.973659	11.5225074	23.1987563	0.4345740	31.1669492
2	1	1	1	8	29.171049	8.2222872	16.9718525	2.2685474	30.7419650
2	1	2	0	6	44.012895	11.5200620	28.7196783	5.9194373	43.2489033
2	1	2	1	5	39.146046	17.1107640	25.7520260	2.7682184	43.9346880
2	1	3	0	5	41.557320	11.6809524	55.8594920	6.1407430	73.6213380
2	2	1	0	12	45.617445	7.9473557	18.3264207	0.0614399	31.1506575
2	2	1	1	8	50.574365	5.5574559	14.4345127	-0.0642786	30.0220237
2	2	2	0	6	46.827357	9.0428478	26.2427457	4.5729246	42.7903300
2	2	2	1	5	42.350140	6.6809272	17.3856160	-0.7982316	42.3686560
2	2	3	0	5	35.550996	13.7125778	39.6584320	5.8858642	71.8584680
2	3	1	0	12	44.220731	11.5264758	23.5177783	3.7767056	32.2187258
2	3	1	1	8	36.180756	9.3901969	17.2307052	2.4971139	30.8321850
2	3	2	0	6	42.386423	11.7770050	27.4573633	3.4211847	42.3425850
2	3	2	1	5	40.560068	11.9086880	21.5931796	1.4698530	43.4114340
2	3	3	0	5	44.328674	15.4767500	46.3435940	6.2171946	72.0282140
2	4	1	0	12	42.758497	9.7197544	21.9538650	-0.4164007	30.9479275
2	4	1	1	8	40.186114	11.0457177	20.5886374	3.9556733	31.1797362
2	4	2	0	6	41.243530	11.8441537	33.6118962	1.0320680	41.3470633
2	4	2	1	5	38.923232	11.1033764	24.6141172	0.0266619	42.7254020
2	4	3	0	5	29.699238	12.2098760	52.8198340	3.4790574	69.6292580
2	5	1	0	12	44.541665	8.8950259	18.5775925	1.8525249	31.7013000
2	5	1	1	8	34.956358	6.1267070	15.5846715	1.7089524	30.5758325
2	5	2	0	6	40.351685	9.6853127	25.9597200	2.6370775	42.0824333
2	5	2	1	5	39.971636	10.8134414	25.0822980	1.4004642	43.3694840
2	5	3	0	5	44.090362	12.2672614	47.2551600	5.6015044	71.6779060
4	1	1	0	12	22.875302	10.1592841	13.0344822	7.1707271	33.3093617
4	1	1	1	8	31.582299	4.9560035	10.8739550	12.9045682	34.1743600
4	1	2	0	6	30.857532	15.1029532	21.1451982	7.8856345	44.4021850
4	1	2	1	5	24.541810	23.5314680	30.9293404	9.5068404	46.8330100
4	1	3	0	5	46.217230	17.7035550	61.5422760	18.1851506	80.3691780
4	2	1	0	12	23.848269	16.5129403	23.8766167	4.1681227	32.3324983
4	2	1	1	8	29.624229	9.0747555	14.7198886	11.1263195	33.4912150
4	2	2	0	6	34.552412	14.1391948	36.1394783	7.7426695	44.7280983
4	2	2	1	5	22.912916	24.4166680	35.7905100	4.2809316	44.3879000
4	2	3	0	5	41.135646	24.5550540	45.3454400	24.8747004	84.6656900
4	3	1	0	12	21.818510	14.2933440	24.5839455	5.3466074	32.7683533
4	3	1	1	8	25.362255	19.3072880	23.8925389	11.6982850	33.3701912
4	3	2	0	6	28.086482	14.7194907	47.3946150	5.2290015	42.6585567
4	3	2	1	5	23.451826	22.1930614	33.0498820	8.3905900	45.9588840
4	3	3	0	5	34.717476	27.3378580	46.6008460	14.6343534	78.3034360
4	4	1	0	12	20.404236	16.8727087	21.0666004	6.7415143	33.2337617
4	4	1	1	8	21.094245	17.7382954	32.4902062	14.9645053	34.7282662
4	4	2	0	6	23.979568	25.8699645	26.9100477	6.5194398	43.2192617
4	4	2	1	5	20.955846	26.3772900	30.5458160	8.7231698	46.3243020
4	4	3	0	5	33.940186	24.5616880	45.2302140	16.7869040	78.8624200
4	5	1	0	12	26.599623	11.0243829	13.9477720	3.2598157	32.0687508
4	5	1	1	8	32.467422	11.1001602	17.6109950	8.0944739	32.5461137
4	5	2	0	6	33.723383	15.1359728	34.6462165	4.8416673	42.6521317
4	5	2	1	5	32.133956	19.7553540	27.3763480	5.8168521	44.9408800
4	5	3	0	5	45.948590	21.2467518	46.7724820	13.7799658	77.8429060
6	1	1	0	12	23.517744	13.8492056	12.7187373	13.5785491	35.5016692
6	1	1	1	8	44.686246	4.2361109	12.9023462	23.3316816	37.0475325

ANALYSIS OF VARIANCE PROCEDURE

MEANS

TBO	LOT	VAR	TYPE	N	COST	SHORT	PERSHORT	DELERR	PERERR
6	1	2	0	6	39.875362	9.7222217	25.4506350	12.1901740	45.4914233
6	1	2	1	5	35.410932	13.2323238	14.6558430	11.8873244	47.2140700
6	1	3	0	5	54.267344	36.4761900	31.3260520	18.0346978	81.7711420
6	2	1	0	12	17.177751	14.6990733	19.2804417	10.5042260	34.4303792
6	2	1	1	8	25.621642	16.7234837	27.4268850	22.4282640	37.2059162
6	2	2	0	6	23.762530	22.8956233	16.7324483	17.8465332	46.3094367
6	2	2	1	5	19.457024	30.7777780	34.2601040	2.7302490	43.7887640
6	2	3	0	5	39.825586	42.9965040	46.8137100	41.3889492	97.9527760
6	3	1	0	12	17.917299	13.7037033	23.1301968	12.0829000	35.0275792
6	3	1	1	8	27.428461	14.1887612	13.4735831	23.6590832	37.5370625
6	3	2	0	6	26.402622	14.9603167	21.2852183	11.0751658	45.1861283
6	3	2	1	5	19.493852	21.9999980	18.0713220	9.3849722	46.5008220
6	3	3	0	5	38.590740	36.8253960	49.3651620	21.6760630	83.8829340
6	4	1	0	12	16.128342	21.9675917	31.3279012	15.6526455	36.1863683
6	4	1	1	8	18.477199	20.8333325	22.4222126	28.8018259	39.1372862
6	4	2	0	6	18.944413	22.6851833	26.9272638	16.4019243	47.2098400
6	4	2	1	5	16.369960	34.4444440	45.3357900	18.8305980	50.5072500
6	4	3	0	5	32.222102	40.5714260	41.8427620	28.7375228	86.0940420
6	5	1	0	12	25.163864	9.9754982	17.1746405	6.3680503	33.1848842
6	5	1	1	8	53.939162	2.9071970	5.8095247	19.0417732	35.4041600
6	5	2	0	6	44.279573	9.0939157	17.3818803	11.8176997	45.8010267
6	5	2	1	5	49.583430	19.2410546	35.0697800	11.0880600	47.2856180
6	5	3	0	5	62.118390	23.8839264	43.1342500	21.1427754	84.0472520
8	1	1	0	12	32.805423	7.0875424	10.1267763	11.2624813	34.6125233
8	1	1	1	8	59.003462	9.1866471	9.3866736	34.7680495	39.2775375
8	1	2	0	6	36.816265	20.3703700	23.7330530	32.6739293	53.7852833
8	1	2	1	5	40.296498	23.8023084	19.3182732	22.9615400	52.1484500
8	1	3	0	5	73.912066	29.6764706	44.5122560	17.3543864	79.4425000
8	2	1	0	12	16.826624	18.6507933	30.9505942	15.6702480	35.6812433
8	2	1	1	8	21.768736	24.7700212	25.2235567	41.6339475	42.4758350
8	2	2	0	6	24.619770	18.2539667	42.6449533	37.3413203	56.1148683
8	2	2	1	5	17.285160	35.7142860	26.7226740	22.2619042	51.8153080
8	2	3	0	5	38.406094	45.1031740	35.3266840	31.5285156	89.0447120
8	3	1	0	12	17.878703	14.6329367	14.5719613	14.1325969	35.4636900
8	3	1	1	8	32.920745	15.4315475	13.7228876	29.1143784	38.7362800
8	3	2	0	6	34.667767	16.3690478	34.4103267	31.7739158	52.6979000
8	3	2	1	5	18.999944	25.0000000	16.5459900	12.6569821	47.6596280
8	3	3	0	5	44.935882	48.6363640	39.1188420	34.3645163	92.2171800
8	4	1	0	12	14.974919	20.4861100	28.9520525	11.5336307	34.8376275
8	4	1	1	8	17.275219	30.0099200	38.6408052	43.9795900	42.8037912
8	4	2	0	6	17.780507	36.5079350	35.0403367	30.0118992	52.2188600
8	4	2	1	5	17.986062	32.5000000	17.7240548	12.7555656	48.0669400
8	4	3	0	5	29.933370	41.4523800	37.6944460	38.8919077	96.2197460
8	5	1	0	12	78.323194	5.9603004	12.5063405	16.0564024	36.3837067
8	5	1	1	8	97.431020	2.0942301	11.7870050	32.4972579	40.4958125
8	5	2	0	6	112.404303	5.2588387	28.7448467	47.1343468	58.7611183
8	5	2	1	5	152.052602	5.7321196	7.6078484	10.4348570	46.8657920
8	5	3	0	5	170.696912	11.6998564	33.8226220	40.7741663	97.2513780
10	1	1	0	12	35.096220	15.2777783	22.2862325	21.5845751	37.6134283
10	1	1	1	8	65.906560	17.0436492	31.4612709	40.0538185	40.4786712
10	1	2	0	6	61.064922	21.5476183	34.3611933	53.4163685	63.2863917
10	1	2	1	5	121.115354	16.1015860	38.2198600	11.7819535	47.2831740

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ANALYSIS OF VARIANCE PROCEDURE

MEANS

TBO	LOT	VAR	TYPE	N	COST	SHORT	PERSHORT	DELERR	PERERR
10	1	3	0	5	154.067180	12.3559468	39.2117460	25.0287268	86.7692560
10	2	1	0	12	15.032989	29.9206342	33.6542769	19.2946565	36.6720958
10	2	1	1	8	17.928786	36.3528137	33.3922904	49.1637475	44.0541600
10	2	2	0	6	19.601488	28.3333333	50.4769433	53.9108195	63.3170663
10	2	2	1	5	14.822866	30.6666640	33.0540800	20.7440059	51.0105540
10	2	3	0	5	27.241050	51.4285720	42.8972440	12.8594764	75.2993720
10	3	1	0	12	14.498465	26.9444450	28.3330208	12.6389357	35.2087756
10	3	1	1	8	35.168067	26.3492069	35.0447440	44.2599700	41.7017287
10	3	2	0	6	24.040148	29.4444450	32.9368515	39.7135813	56.6177333
10	3	2	1	5	22.659892	31.4285680	20.0157500	15.8333502	49.1981940
10	3	3	0	5	52.069566	37.5259740	44.2174960	4.0446172	66.0354740
10	4	1	0	12	12.519354	26.9444450	39.4173164	24.6585457	38.5641800
10	4	1	1	8	14.483524	40.8928562	40.5792050	59.6146937	47.7926950
10	4	2	0	6	18.053757	25.0000000	52.2866700	40.9312448	56.6747500
10	4	2	1	5	14.832940	37.9999980	29.7577580	12.5060667	47.6966580
10	4	3	0	5	27.378848	53.3333300	53.5211580	19.6828360	79.0061200
10	5	1	0	12	368.291683	0.2777777	3.1250000	24.7492242	39.4518125
10	5	1	1	8	282.007750	0.5000000	8.9285712	37.5054352	41.8290562
10	5	2	0	6	284.913433	0.5555555	13.8888883	48.2842210	58.1565650
10	5	2	1	5	346.232920	0.0000000	0.0000000	8.3550868	46.4794160
10	5	3	0	5	306.077680	1.7142858	15.7777774	34.8773286	93.1520580

APPENDIX E

ANOVA RESULTS -- GROUP II DATA

The following text provides the code used in the SAS routine. Output consists of all subsequent pages.

```
DATA;
INPUT SET TYPE VAR COFVAR TBO LOT COST SHORT
PERSHORT DELERR PERERR BIAS;
DROP TYPE VAR COFVAR BIAS;
CARDS;
;
PROC ANOVA;
    CLASS SET TBO LOT;
    MODEL COST SHORT PERSHORT DELERR PERERR =  LOT TBO
          SET LOT*TBO LOT*SET TBO*SET;
    MEANS LOT / TUKEY E=LOT*SET;
    MEANS TBO / TUKEY E=TBO*SET;
    MEANS SET LOT*TBO LOT*SET TBO*SET / TUKEY;
    TEST H=LOT E=LOT*SET;
    TEST H=TBO E=TBO*SET;
    OUTPUT OUT=PLOTDATA P=YPRED R=YRESID;
PROC UNIVARIATE NORMAL PLOT;
    VAR YRESID;
PROC PLOT;
    PLOT YRESID*YPRED;
    PLOT YRESID*LOT;
    PLOT YRESID*TBO;
```

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GENERAL LINEAR MODELS PROCEDURE

CLASS LEVEL INFORMATION

CLASS	LEVELS	VALUES
SET	5	1 2 3 4 5
TBO	5	2 4 6 8 10
LOT	5	1 2 3 4 5

NUMBER OF OBSERVATIONS IN DATA SET = 125

SAS 13:07 TUESDAY MAY [illegible] 1989 [illegible]

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: COST

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	60	565030.40037689	9417.17333961	20.27	0.0001	0.950001	42.4290
ERROR	64	29737.76416453	464.65256507		ROOT MSE		COST MEAN
CORRECTED TOTAL	124	594768.16454142			21.55580119		50.80435250

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
LOT	4	170805.81714428	91.90	0.0001	4	170805.81714428	91.90	0.0001
TBO	4	91516.99144414	49.24	0.0001	4	91516.99144414	49.24	0.0001
SET	4	6459.49272261	3.48	0.0124	4	6459.49272261	3.48	0.0124
TBO*LOT	16	246895.12529861	33.21	0.0001	16	246895.12529861	33.21	0.0001
SET*LOT	16	27499.52674268	3.70	0.0001	16	27499.52674268	3.70	0.0001
SET*TBO	16	21853.44702457	2.94	0.0011	16	21853.44702457	2.94	0.0011

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GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: SHORT

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	60	16197.45899103	269.95764985	3.19	0.0001	0.749508	56.2294
ERROR	64	5413.32004373	84.58312568		ROOT MSE		SHORT MEAN
CORRECTED TOTAL	124	21610.77903476			9.19690849		16.35604909

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
LOT	4	4589.73863595	13.57	0.0001	4	4589.73863595	13.57	0.0001
TBO	4	3084.87242157	9.12	0.0001	4	3084.87242157	9.12	0.0001
SET	4	380.04155767	1.12	0.3534	4	380.04155767	1.12	0.3534
TBO*LOT	16	4442.28461492	3.28	0.0004	16	4442.28461492	3.28	0.0004
SET*LOT	16	2040.80953608	1.51	0.1247	16	2040.80953608	1.51	0.1247
SET*TBO	16	1659.71222483	1.23	0.2736	16	1659.71222483	1.23	0.2736

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GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: PERSHORT

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	60	36687.66279924	611.46104665	2.30	0.0006	0.683531	59.3199
ERROR	64	16986.08641667	265.40760026		ROOT MSE		PERSHORT MEAN
CORRECTED TOTAL	124	53673.74921591			16.29133513		27.46351057

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
LOT	4	4415.85882667	4.16	0.0047	4	4415.85882667	4.16	0.0047
TBO	4	3417.49857628	3.22	0.0180	4	3417.49857628	3.22	0.0180
SET	4	4955.99287772	4.67	0.0023	4	4955.99287772	4.67	0.0023
TBO*LOT	16	4391.22395875	1.03	0.4349	16	4391.22395875	1.03	0.4349
SET*LOT	16	9261.27823573	2.18	0.0146	16	9261.27823573	2.18	0.0146
SET*TBO	16	10245.81032408	2.41	0.0067	16	10245.81032408	2.41	0.0067

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GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: DELERR

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	60	45730.57998833	762.17633314	3.04	0.0001	0.740138	61.7653
ERROR	64	16056.00994200	250.87515534		ROOT MSE		DELERR MEAN
CORRECTED TOTAL	124	61786.58993033			15.83903897		25.64392810

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
LOT	4	1238.06194197	1.23	0.3055	4	1238.06194197	1.23	0.3055
TBO	4	17706.37837519	17.64	0.0001	4	17706.37837519	17.64	0.0001
SET	4	12737.24578276	12.69	0.0001	4	12737.24578276	12.69	0.0001
TBO*LOT	16	1345.14003183	0.34	0.9911	16	1345.14003183	0.34	0.9911
SET*LOT	16	7350.04017087	1.83	0.0459	16	7350.04017087	1.83	0.0459
SET*TBO	16	5353.71368571	1.33	0.2053	16	5353.71368571	1.33	0.2053

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GENERAL LINEAR MODELS PROCEDURE

DEPENDENT VARIABLE: PERERR

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PR > F	R-SQUARE	C.V.
MODEL	60	13415.78812311	223.59646872	7.63	0.0001	0.877363	14.4659
ERROR	64	1875.25089257	29.30079520		ROOT MSE		PERERR MEAN
CORRECTED TOTAL	124	15291.03901568			5.41302089		37.41906584

SOURCE	DF	TYPE I SS	F VALUE	PR > F	DF	TYPE III SS	F VALUE	PR > F
LOT	4	142.06486092	1.21	0.3144	4	142.06486092	1.21	0.3144
TBO	4	1701.34034705	14.52	0.0001	4	1701.34034705	14.52	0.0001
SET	4	9919.78741060	84.64	0.0001	4	9919.78741060	84.64	0.0001
TBO*LOT	16	148.12926649	0.32	0.9935	16	148.12926649	0.32	0.9935
SET*LOT	16	853.60554973	1.82	0.0474	16	853.60554973	1.82	0.0474
SET*TBO	16	650.85968830	1.39	0.1763	16	650.85968830	1.39	0.1763

GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: COST
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE.
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=16 MSE=1718.72
CRITICAL VALUE OF STUDENTIZED RANGE=4.333
MINIMUM SIGNIFICANT DIFFERENCE=35.924

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	LOT
A	121.43	25	5
B	54.29	25	1
B			
B	26.92	25	4
B			
B	25.77	25	3
B			
B	25.62	25	2

```
                    SAS                         [illegible] TUESDAY  MAY [illegible]    6

          GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: SHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

        ALPHA=0.05  DF=16  MSE=127.551
        CRITICAL VALUE OF STUDENTIZED RANGE=4.333
        MINIMUM SIGNIFICANT DIFFERENCE=9.7863

 MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

     TUKEY   GROUPING              MEAN      N  LOT

                  A              22.137     25  2
                  A
                  A              21.270     25  3
                  A
                  A              19.551     25  4
                  A
             B    A              12.523     25  1
             B
             B                    6.300     25  5
```

```
                          SAS                          13:27 TUESDAY, MAY 2, 1989   9

              GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERSHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

        ALPHA=0.05  DF=16  MSE=578.83
        CRITICAL VALUE OF STUDENTIZED RANGE=4.333
        MINIMUM SIGNIFICANT DIFFERENCE=20.847

 MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

      TUKEY   GROUPING            MEAN      N  LOT

                    A           33.874     25  4
                    A
                    A           31.921     25  2
                    A
                    A           29.800     25  3
                    A
                    A           24.257     25  1
                    A
                    A           17.467     25  5
```

GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: DELERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=16 MSE=459.378
CRITICAL VALUE OF STUDENTIZED RANGE=4.333
MINIMUM SIGNIFICANT DIFFERENCE=18.572

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	LOT
A	29.016	25	1
A			
A	28.264	25	3
A			
A	26.742	25	2
A			
A	23.671	25	4
A			
A	20.526	25	5

```
                    SAS                              13:27 TUESDAY, MAY 2, 1989

            GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

       ALPHA=0.05  DF=16  MSE=53.3504
       CRITICAL VALUE OF STUDENTIZED RANGE=4.333
       MINIMUM SIGNIFICANT DIFFERENCE=6.3292

 MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

     TUKEY    GROUPING              MEAN      N  LOT

                     A            38.938     25  1
                     A
                     A            38.168     25  3
                     A
                     A            37.452     25  2
                     A
                     A            36.474     25  4
                     A
                     A            36.044     25  5
```

SAS 13:0? TUESDAY, MAY ? 1989 ??

GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: COST
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE.
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=16 MSE=1365.84
CRITICAL VALUE OF STUDENTIZED RANGE=4.333
MINIMUM SIGNIFICANT DIFFERENCE=32.024

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	TBO
A	102.15	25	10
B	53.24	25	8
B			
B	38.05	25	2
B			
B	32.88	25	6
B			
B	27.70	25	4

```
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            GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: SHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

        ALPHA=0.05  DF=16  MSE=103.732
        CRITICAL VALUE OF STUDENTIZED RANGE=4.333
        MINIMUM SIGNIFICANT DIFFERENCE=6.8254

 MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

      TUKEY   GROUPING              MEAN      N  TBO

                    A             22.355     25  10
                    A
                    A             19.872     25  8
                    A
                    A             16.927     25  6
                    A
               B    A             14.766     25  4
               B
               B                   7.659     25  2
```

GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERSHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE.
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=16 MSE=640.363
CRITICAL VALUE OF STUDENTIZED RANGE=4.333
MINIMUM SIGNIFICANT DIFFERENCE=21.928

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	TBO
A	35.861	25	10
A			
A	30.453	25	8
A			
A	26.205	25	6
A			
A	23.877	25	2
A			
A	20.921	25	4

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GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: DELERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=16 MSE=334.607
CRITICAL VALUE OF STUDENTIZED RANGE=4.333
MINIMUM SIGNIFICANT DIFFERENCE=15.851

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY	GROUPING	MEAN	N	TBO
	A	38.478	25	10
	A			
	A	37.083	25	8
	A			
B	A	26.033	25	6
B				
B	C	20.675	5	4
	C			
	C	5.950	25	2

```
                    SAS                                   13:27 TUESDAY, MAY 2, 1989   16

          GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

        ALPHA=0.05  DF=16  MSE=40.6787
        CRITICAL VALUE OF STUDENTIZED RANGE=4.333
        MINIMUM SIGNIFICANT DIFFERENCE=5.5266

 MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

     TUKEY    GROUPING              MEAN      N  TBC

                    A             41.435     25  10
                    A
                    A             41.056     25  8
                    A
                    A             37.276     25  6
                    A
              B     A             35.949     25  4
              B
              B                   31.377     25  2
```

```
                    SAS                          [illegible] TUESDAY, MAY [illegible] [illegible]

          GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: COST
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

        ALPHA=0.05  DF=64  MSE=464.653
        CRITICAL VALUE OF STUDENTIZED RANGE=3.970
        MINIMUM SIGNIFICANT DIFFERENCE=17.114

 MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

      TUKEY    GROUPING           MEAN      N  SET

                   A            60.157     25  4
                   A
                   A            58.958     25  3
                   A
                   A            45.910     25  2
                   A
                   A            45.182     25  1
                   A
                   A            43.914     25  5
```

GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: SHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=64 MSE=84.5831
CRITICAL VALUE OF STUDENTIZED RANGE=3.970
MINIMUM SIGNIFICANT DIFFERENCE=7.3019

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	SET
A	19.389	25	3
A			
A	16.937	25	4
A			
A	16.026	25	2
A			
A	15.005	25	5
A			
A	14.424	25	1

```
                    SAS                        [illegible] TUESDAY  MAY 1 [illegible]   19

          GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERSHORT
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

        ALPHA=0.05  DF=64  MSE=265.406
        CRITICAL VALUE OF STUDENTIZED RANGE=3.[illegible]
        MINIMUM SIGNIFICANT DIFFERENCE=1[illegible].934

MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

     TUKEY   GROUPING           MEAN      N  SET

                   A          36.613     25  5
                   A
             B     A          3[illegible].699     25  4
             B     A
             B     A          27.439     25  2
             B
             B                22.699     25  3
             B
             B                16.866     25  1
```

```
                                SAS                        13:27 TUESDAY  MAY 2  1989   20

                 GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: DELERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE,
      BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

         ALPHA=0.05  DF=64  MSE=250.875
         CRITICAL VALUE OF STUDENTIZED RANGE=3.970
         MINIMUM SIGNIFICANT DIFFERENCE=12.575

 MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

      TUKEY    GROUPING              MEAN      N  SET

                     A             36.232     25  4
                     A
               B     A             32.114     25  2
               B     A
               B     A             27.658     25  1
               B
               B                   21.555     25  5

                     C              8.662     25  3
```

GENERAL LINEAR MODELS PROCEDURE

TUKEY'S STUDENTIZED RANGE (HSD) TEST FOR VARIABLE: PERERR
NOTE: THIS TEST CONTROLS THE TYPE I EXPERIMENTWISE ERROR RATE.
BUT GENERALLY HAS A HIGHER TYPE II ERROR RATE THAN REGWQ

ALPHA=0.05 DF=64 MSE=29.3008
CRITICAL VALUE OF STUDENTIZED RANGE=3.970
MINIMUM SIGNIFICANT DIFFERENCE=4.2976

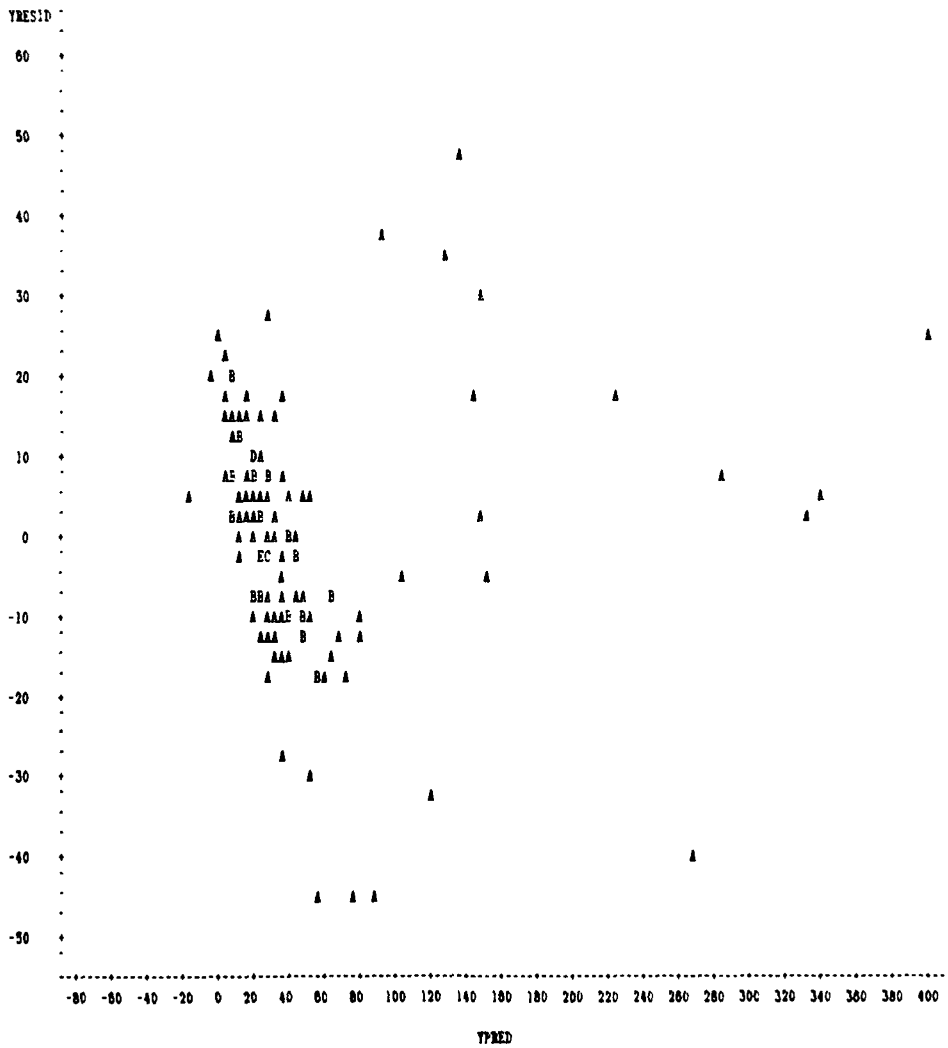
MEANS WITH THE SAME LETTER ARE NOT SIGNIFICANTLY DIFFERENT.

TUKEY GROUPING	MEAN	N	SET
A	52.717	25	2
B	39.114	25	4
B			
B	36.155	25	5
C	29.608	25	1
C			
C	27.502	25	3

```
                                              SAS                     13:27 TUESDAY MAY 2, 1989   22

                                          UNIVARIATE

VARIABLE=YRESID

             MOMENTS                                    QUANTILES(DEF=4)                          EXTREMES

N               125  SUM WGTS        125      100% MAX    46.434    99%    44.3288          LOWEST    HIGHEST
MEAN      6.472E-13  SUM       8.091E-11       75% Q3    8.45969    95%    25.2995        -45.9912    28.3848
STD DEV     15.4861  VARIANCE    239.821       50% MED  0.729911    90%    17.8527        -45.9433    31.0922
SKEWNESS  -0.250999  KURTOSIS    1.43372       25% Q1   -8.99172    10%   -16.2704        -43.9996    34.0022
USS         29737.8  CSS         29737.8        0% MIN  -45.9912     5%   -29.1132         -39.847    38.3373
CV            99999  STD MEAN    1.38512                             1%   -45.9787         -31.444     46.434
T:MEAN=0  4.673E-13  PROB>|T|          1      RANGE      92.4252
SGN RANK       64.5  PROB>|S|     0.8747      Q3-Q1      17.4514
NUM ^= 0        125                           MODE      -45.9912
D:NORMAL  0.0755447  PROB>D         0.08

STEM LEAF                    #          BOXPLOT                         NORMAL PROBABILITY PLOT
   4 6                       1             0              47.5+                                                 *
   4                                                          |
   3 8                       1             0                  |                                              ****
   3 14                      2             |                  |                                           ****
   2 68                      2             |                  |                                         ***
   2 0134                    4             |                  |                                     ****
   1 566678889               9             |                  |                                  *****
   1 011123444               9             |                  |                              +***
   0 55556677777788899      17          +-----+               |                           ****
   0 1111112222223344444    19          *--+--*               |                       *****
  -0 433222222221110        15          |     |               |                    ***
  -0 9999888777766665       16          +-----+               |                ****
  -1 444433321100000        15             |                  |           *****+
  -1 77777666                8             |                  |        *****+
  -2                                       |                  |       ++++
  -2 7                       1             |                  |    ++++
  -3 10                      2             |                  | +++ **
  -3                                       0                  |+++  *
  -4 40                      2             0                  |    *
  -4 66                      2             0             -47.5+*  *
     ----+----+----+----+                                     +----+----+----+----+----+----+----+----+----+----+
 MULTIPLY STEM.LEAF BY 10**+01                                     -2        -1         0        +1        +2
```

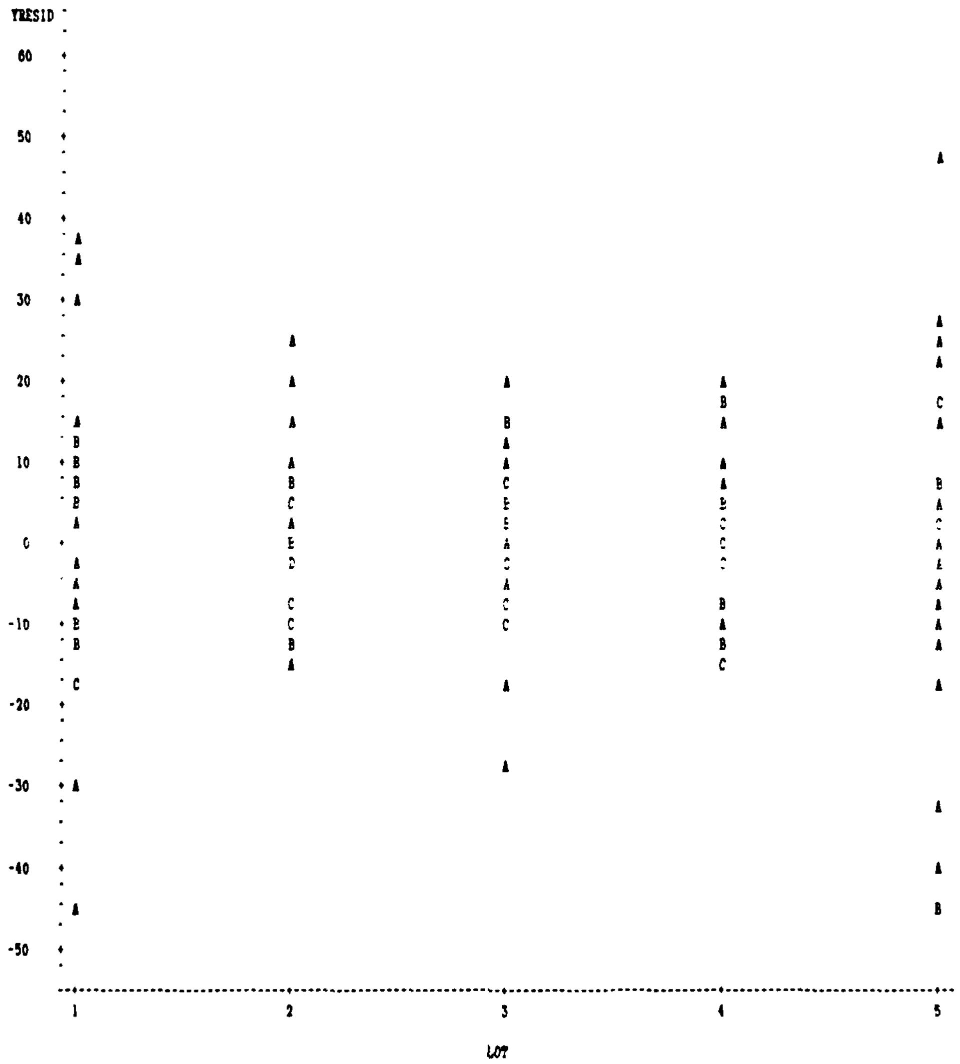
SAS 13:27 TUESDAY, MAY 2, 1989 23

PLOT OF YRESID*YPRED LEGEND: A = 1 OBS, B = 2 OBS, ETC.



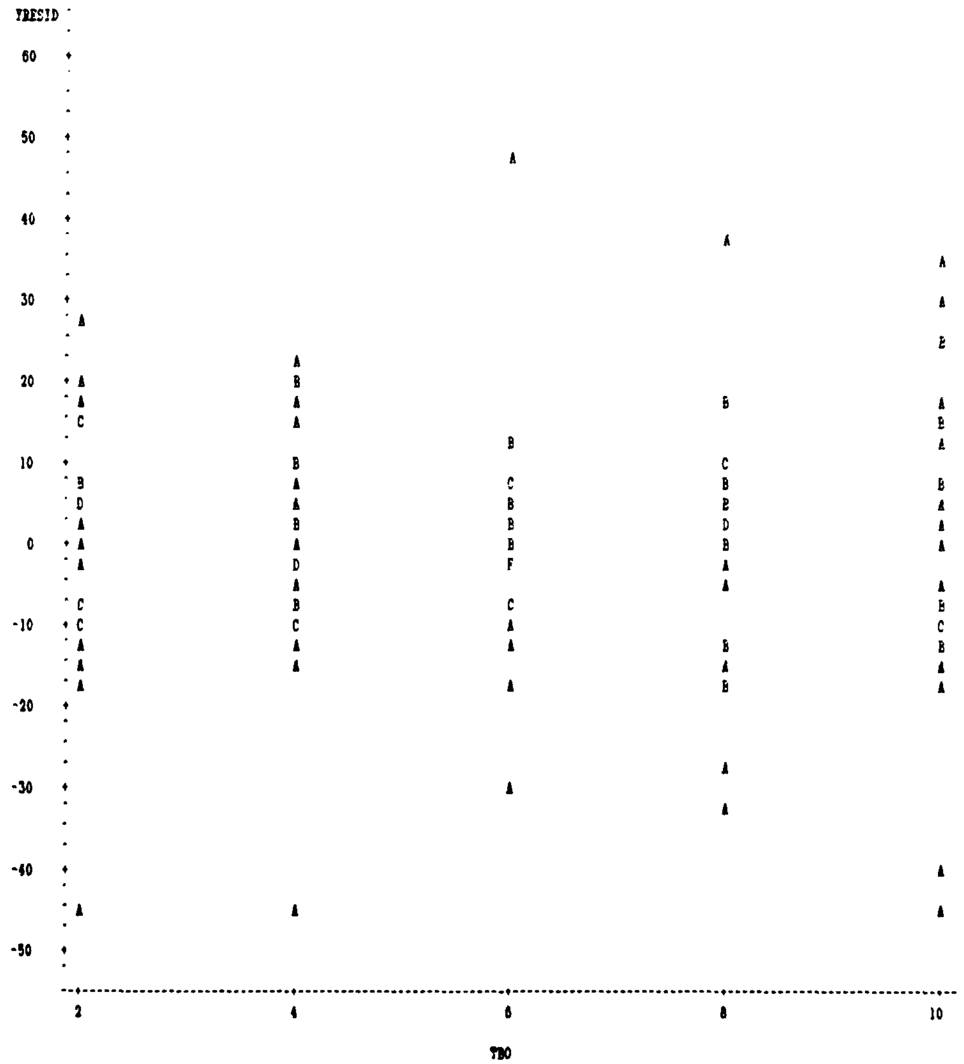
SAS 13:27 TUESDAY, MAY 2, 1989 24

PLOT OF YRESID*LOT LEGEND: A = 1 OBS, B = 2 OBS, ETC.



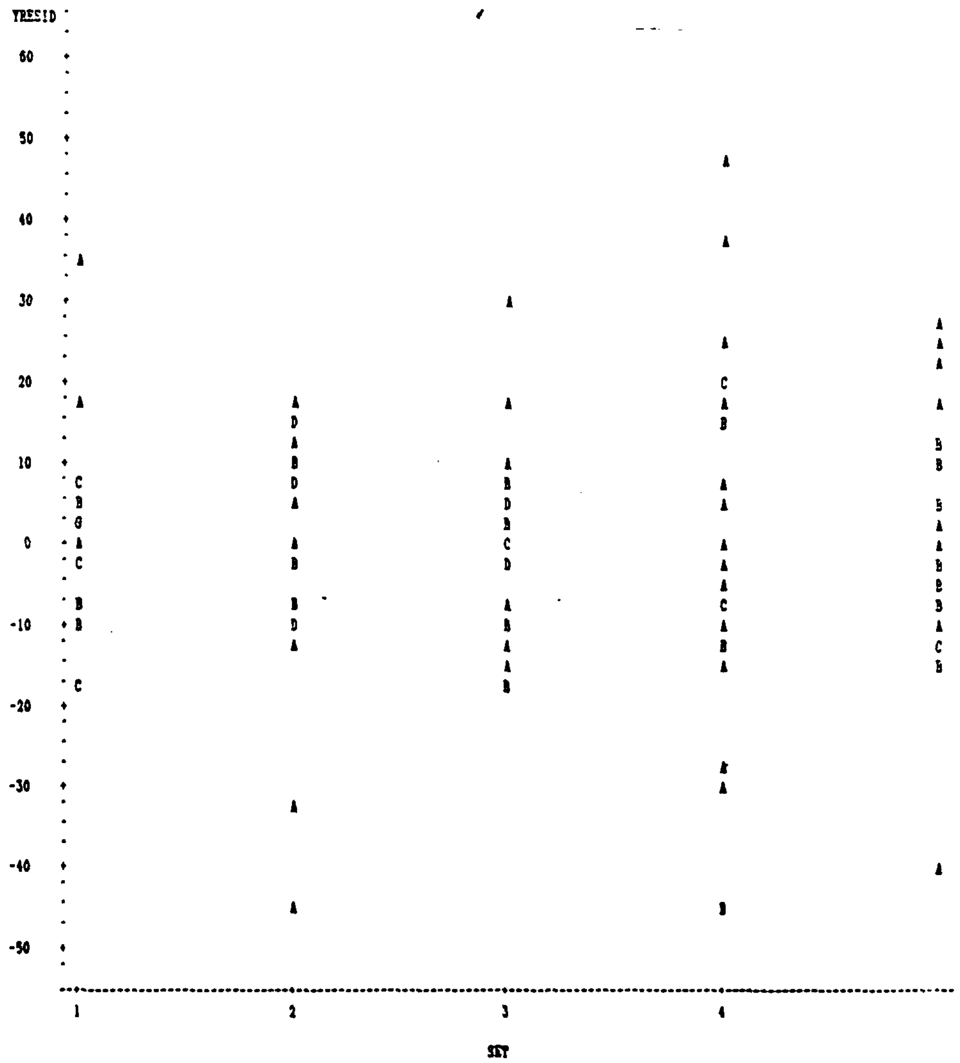
SAS 13:27 TUESDAY, MAY 2, 1989 25

PLOT OF YRESID*TBO LEGEND: A = 1 OBS, B = 2 OBS, ETC.



SAS 13:27 TUESDAY, MAY 2, 1989 26

PLOT OF YRESID*SET LEGEND: A = 1 OBS, B = 2 OBS, ETC.



END